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A double-sampling approach to deriving training and validation data for remotely-sensed vegetation products

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The need for large sample sizes to train, calibrate, and validate remote-sensing products has driven an emphasis towards rapid, and in many cases qualitative, field methods. Double-sampling is an option for calibrating less precise field measurements with data from a more precise method collected at a subset of sampling locations. While applicable to the creation of training and validation datasets for remote-sensing products, double-sampling has rarely been used in this context. Our objective was to compare vegetation indicators developed from a rapid qualitative (i.e. ocular estimation) field protocol with the quantitative field protocol used by the Bureau of Land Management's Assessment, Inventory and Monitoring (AIM) programme to determine whether double-sampling could be used to adjust the qualitative estimates to improve the relationship between rapidly collected field data and high-resolution satellite imagery. We used beta regression to establish the relationship between the quantitative and qualitative estimates of vegetation cover from 50 field sites in the Piceance Basin of northwestern Colorado, USA. Using the defined regression models for eight vegetation indicators we adjusted the qualitative estimates and compared the results, along with the original measurements, to 5 m-resolution RapidEye satellite imagery. We found good correlation between quantitative and ocular estimates for dominant site components such as shrub cover and bare ground, but low correlations for minor site components (e.g. annual grass cover) or indicators where observers were required to estimate over multiple life forms (e.g. total canopy cover). Using the beta-regression models to adjust the qualitative estimates with the quantitative data significantly improved correlation with the RapidEye imagery for most indicators. As a means of improving training data for remote-sensing projects, double-sampling should be used where a strong relationship exists between quantitative and qualitative field techniques. Accordingly, ocular techniques should be used only when they can generate reliable estimates of vegetation cover.

1. Introduction

The use of remotely sensed imagery is expected to improve the efficiency, reliability, and frequency of assessment and monitoring of arid and semi-arid landscapes (Booth and Tueller 2003; Washington-Allen et al. 2006; Weber 2006; Hunt et al. 2003). Four typical remote sensing applications to environmental assessment and monitoring are: image

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interpretation by trained observers (e.g. Booth and Cox 2008; Booth et al. 2003; Duniway et al. 2011), classification of imagery into discrete land-use or land-cover categories (e.g. Laliberte et al. 2010; Blaschke, Conradi, and Lang 2002; Kennedy et al. 2009), interpretation of spectral indices related to vegetation properties (e.g. Washington-Allen et al. 2006; Wylie, Boyte, and Major 2012), and prediction of continuous vegetation attributes (i.e. continuous fields) such as vegetation cover or density (Homer et al. 2012; e.g. Karl 2010). This study focuses on the role of field data in the development and use of continuous-fields products for environmental assessment and monitoring.

While some continuous-fields approaches focus on the development and use of biophysical models that, once calibrated, do not require the use of field data for their application (e.g. Marsett et al. 2006; Qi et al. 1994; Reeves, Zhao, and Running 2006; Running et al. 2004), many remote-sensing techniques for continuous-fields prediction require *in situ* measurements to train, calibrate, and validate image-derived products. Ground-condition measurements for remote-sensing projects have been collected using a wide array of ground-based and aerial measurements (McCoy 2005). These include field-based vegetation measurements via quantitative, semi-quantitative (e.g. ordinal or nominal), or qualitative (e.g. ocular estimation) methods. Regardless of the technique used, collection of training or validation data *in situ* is seen as being expensive (Pellant, Shaver, and Spaeth 1999), and given the large, diverse landscapes covered by many remote sensing projects, large training sample sets are often required (see McCoy (2005) for guidance on sample sizes for remote-sensing projects).

This need for large sample sizes to train, calibrate, and validate remote-sensing products has driven an emphasis towards rapid, and in many cases, qualitative field methods (Petersen, Stringham, and Roundy 2009; Marsett et al. 2006; Homer et al. 2012; e.g. Knick, Rotenberry, and Zarriello 1997; Homer et al. 2008). Treitz et al. (1992) and Weber (2006) looked at differences between using qualitative and quantitative data to define land-cover classes for image classification and concluded that qualitative approaches produced classes that could be mapped more accurately. But the appropriateness of qualitative data to develop or test continuous-fields models of vegetation in semi-arid and arid environments from remote-sensing data has not been thoroughly explored.

Studies comparing qualitative and quantitative measures of vegetation attributes in the field have produced mixed results. Some studies have reported that qualitative measures (e.g. ocular estimates) of vegetation attributes perform as well as quantitative measures (Seefeldt and Booth 2006; Booth et al. 2006; Stohlgren, Bull, and Otsuki 1998; Dethier et al. 1993). Others have reported that qualitative measures are biased and less precise (Hanley 1978; Kennedy and Addison 1987; Bergstedt, Westerberg, and Milberg 2009; Floyd and Anderson 1987; Korhonen et al. 2006). Variation between qualitative and quantitative measures has been attributed to factors such as plot size, spatial distribution of vegetation within the measurement area, overall vegetation cover, plant morphology, and observer experience (Korhonen et al. 2006; Klimes 2003; Neeser et al. 2000; Andujar et al. 2010; Floyd and Anderson 1987). Beyond the basic assumption that poor-quality input data can lead to poor remote-sensing products (i.e. 'garbage-in: garbage-out'), little study has been done on the effects of imprecision of input data on the accuracy of continuous-fields remote-sensing products.

One option for balancing the need for high-quality input data for remote-sensing projects with the need to sample a large number of locations across a diversity of plant communities could be to employ a two-phase sampling approach. Two-phase sampling, also called double-sampling, is often used when the variable of interest is difficult to measure directly or expensive to measure precisely, but a related variable or less precise

method exists that can be easily or quickly implemented (Lohr 2009; Thompson 2002). The first sampling phase consists of a large and relatively inexpensive set of measurements. The second phase consists of more precise measurements made at a subset of the first-phase locations. The more accurate or precise second-phase data are then used to improve estimates made from the first phase through ratio or regression estimators.

Double-sampling is a common technique in many ecological studies to calibrate less precise field measurements with more accurate procedures (e.g. Ahmed, Bonham, and Laycock 1983; Bart, Earnst, and Murphy 2002; Köhl, Magnussen, and Marchetti 2006; Elzinga, Salzer, and Willoughby 1998). Double-sampling has also been applied to remote-sensing studies. Maxwell (1976) and Wylie et al. (1991) used double-sampling of vegetation measurements within plots to generate estimates of vegetation properties (e.g. biomass). Stehman (1996) and Kalkhan, Reich, and Stohlgren (1998) used double-sampling to evaluate the accuracy of classified images. Eva and Lambin (1998) and Parker and Evans (2004) proposed using a double-sampling approach using less precise remotely sensed indicators in combination with more accurate field-measured indicators for landscape inventory and monitoring. Duniway et al. (2011) and Karl et al. (2012) proposed using double-sampling to calibrate estimates of vegetation cover derived from very large-scale aerial imagery. However, few remote-sensing studies actually implement a double-sampling protocol to obtain field measurements for image training in a cost-effective manner where a set of sites sampled with a less precise method (e.g. qualitative measurements) is corrected with more precise data collected at a subset of those sites.

Our goal for this study was to evaluate a double-sampling approach to collecting field data to train remote-sensing imagery. Our first objective was to compare vegetation indicators developed from a rapid, qualitative protocol with more rigorous, quantitative protocols. Comparisons were then made between the field methods and against high-resolution satellite imagery. Our second objective was to develop double-sampling regression equations to improve the relationship between the rapid field measurements and imagery.

2. Study area

This study was conducted in a 243,700 ha portion of the Piceance Basin of northwest Colorado (39.824° N, 108.297° W, Figure 1). This area is characterized by deep valleys and high plateaus (Taylor 1987), and comprises primarily the Piceance Creek and Yellow Creek drainages – tributaries of the White River. Elevation in the study area ranges from 1650 to 2820 m (from United States Geologic Survey 1/3 arc-second National Elevation Dataset, <http://ned.usgs.gov>, accessed 16 January 2013). Average annual precipitation for the Meeker, CO, weather station (approximately 10 km northeast of the study area) from 1981 to 2010 was 443 mm (National Oceanic and Atmospheric Administration, National Climate Data Center, <http://www.ncdc.noaa.gov/land-based-station-data/climate-data-online>, accessed 16 January 2013).

Vegetation in the Piceance Basin is a mosaic of pinyon/juniper (*Pinus edulis* Engelm./*Juniperus osteosperma* Torr.) and sagebrush (*Artemisia* spp. L.) shrublands on the slopes and plateaus. The southern portion of the study area has extensive aspen (*Populus tremuloides* Michx.) woodlands on north-facing slopes. Drainage bottoms are typically riparian areas dominated by cottonwood (*Populus* L.) and alder (*Alnus* Mill.).

The study area is approximately 70% in public ownership and 30% privately owned. The US Department of Interior Bureau of Land Management (BLM) is the primary public land steward, managing 165,400 ha (67.9% of the study area). The BLM-managed lands

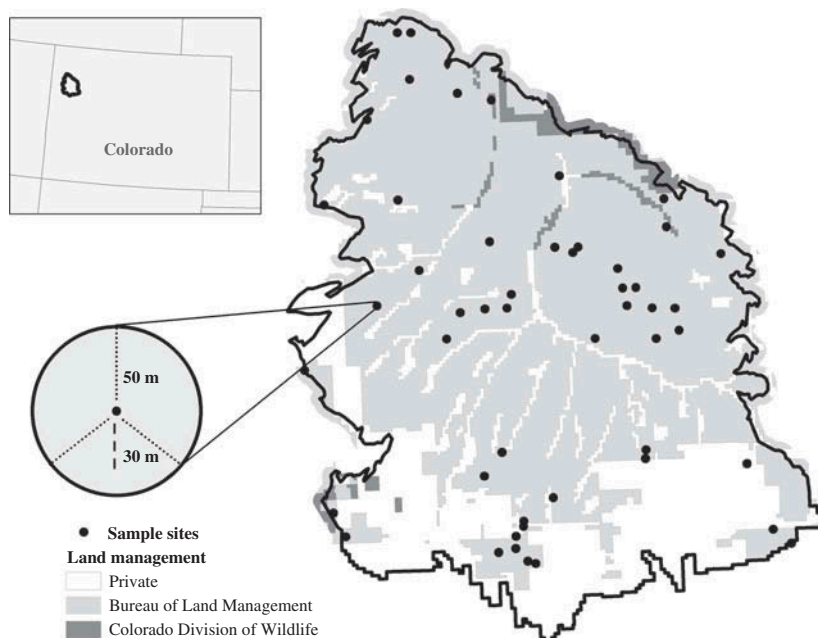


Figure 1. Location of the Piceance Basin study area in northwestern Colorado, USA. Geographical coordinates: 39.824° N, 108.297° W.

in the Piceance Basin are an important source of oil shale deposits (Taylor 1987) and the BLM issues permits for oil and natural gas extraction in the area. Changing conditions in the energy sector and development of new oil and gas extraction technologies have greatly expanded the potential number of new oil and gas well pads in the Piceance Basin (Bureau of Land Management 2012). As part of its land management responsibilities, the BLM is required to measure and monitor the direct and indirect impacts of oil and gas development on the vegetation, soils, water, and wildlife in the Piceance Basin. Accomplishing this over such a large area is a challenging endeavour that could be supported by remote-sensing technologies.

3. Methods

3.1. Image acquisition and processing

RapidEye multispectral satellite imagery was acquired for the study area in June of 2010 and 2011. Dates close to the summer solstice were selected to minimize topographic shading. Due to above-average precipitation and a cool spring, 2011 experienced a high snowpack that was visible in the RapidEye imagery – obscuring many of the sample sites. For this reason, we used the 2010 imagery even though it was acquired a year prior to the field data (see below). The above-average precipitation in 2011 could have resulted in less bare ground and greater cover of grasses and forbs that might affect correlations between the field data and imagery collected a year earlier. However, this should affect data from both methods similarly, and as no significant changes in management or disturbances (e.g. fire) occurred at the sample sites between the image acquisition in 2010 and the field

sampling in 2011, the use of 2010 imagery was deemed acceptable. Image acquisition was completed in two passes – 7 June 2010 and 15 June 2010.

The RapidEye satellite images are from a 5-band multispectral sensor with bands sampling the blue (440–510 nm), green (520–590 nm), red (630–685 nm), red-edge (690–730 nm), and near-infrared (760–850 nm) wavelengths (<http://www.rapideye.com/products/ortho.htm>, date accessed 22 October 2012). The imagery was processed by RapidEye AG (Berlin, Germany) to their Level 3A, which included radiometric and geometric corrections and resampling to a 5 m ground-sampling distance (i.e. resolution) for 25 km² tiles. Average horizontal positional accuracy for the 11 tiles comprising the study area was reported at 17.2 m. Image tiles within dates were merged together. The merged images were then histogram-matched based on overlapping areas and mosaicked into a single image for the study area using ERDAS Imagine Mosaic Pro (<http://geospatial.intergraph.com>, date accessed 18 March 2013). We calculated the average and standard deviation of pixel values for each band within a 55 m radius of each field sample location to correspond to the size of the field measurement plots.

3.2. Sample design

Because the objective of this study was to determine whether data collected using an intensive, quantitative field protocol could be used to improve estimates of indicators made from a rapid, qualitative method and the statistical relationship between those qualitative estimates and the RapidEye imagery, we considered only the second sampling phase where both data collection methods were employed. For this second sampling phase, vegetation measurements were made at 50 locations using a stratified random sampling procedure.

To ensure representation of the diversity of conditions within the study area, field sampling was stratified by plant community potential. Using descriptions of plant community potential from the area's soil surveys (USDA Soil Conservation Service 1982, 1985; USDA Natural Resources Conservation Service 2003), we defined nine plant community strata (Table 1) on the basis of compositional (e.g. soils, precipitation, and reference plant communities) and functional (i.e. types of ecological and management processes) characteristics. Expected distribution of these plant communities in the study area was mapped from the 1:24,000 soil map data (Soil Survey Staff 2008a, 2008b, 2008c) to create sampling strata. Within each stratum, sample locations were selected via a spatially balanced random sampling process (see Theobald et al. 2007). Strata were

Table 1. Strata developed for the study area based on plant-community potential.

Stratum	Number of sites sampled
Aspen woodland	4
Brushy loam	5
Dry exposure	4
Loamy slopes	9
Mountain loam	4
Pinon-juniper woodland	13
Riparian & swales	3
Rolling loam	4
Stoney foothills	4

sampled roughly in proportion to their area in the study area with a minimum of three sites per stratum (Table 1).

3.3. Field data collection

At each sample location within the study area, vegetation measurements were taken following two protocols: the quantitative protocol used by the BLM Assessment, Inventory, and Monitoring programme (AIM protocol, Mackinnon et al. 2011) and a rapid visual-estimation protocol described by Homer et al. (2012) that was designed to collect data for training and validation of remote-sensing products (ocular protocol). Field sampling was conducted between 29 June and 13 September 2011.

Different transects were used for the quantitative and ocular protocols to minimize issues with disturbing vegetation with one technique before measuring it with the other. Because the two protocols were considered to provide site-level estimates (i.e. the sample unit for this study was the site), the use of different transects within the site was considered acceptable.

Relative to this study, the quantitative (i.e. AIM) protocol consisted of three 50 m line-point-intercept (LPI) transects radiating from the centre of the site as described by Herrick et al. (2009, Figure 1). Transects were oriented at 120°, 240°, and 360°. The start of each transect was offset 5 m from the centre point to minimize effects due to trampling. At each 1 m along the transect line, a thin (~1 mm diameter) pin was lowered to the ground and living and dead vegetation touching the pin was recorded as canopy layers. All plants were recorded to the species level except for sagebrush, which was recorded to the subspecies level. Each species intercepted by the pin was recorded only once in the order from top to bottom. Intercepts of overhead vegetation (e.g. trees) were determined by using a sighting tube held perpendicular to the ground (determined using bubble levels embedded in the tube) and sighting through crosshairs. The surface of the ground under the canopy layers (e.g. bare soil, rock, moss) was also recorded. Litter (i.e. detached plant material) was recorded as a canopy layer.

We followed Herrick et al. (2009) for calculation of plant cover indicators from line-point intercept data. Species-level information was aggregated to major life form (i.e. tree, shrub, perennial grass, annual grass), and cover of each life form was calculated as the number of life form 'hits' divided by the total number of pin-drops (150) along all transects at the site. Cover of sagebrush was calculated separately because of its importance to greater sage-grouse (*Centrocercus urophasianus*) habitat (Crawford et al. 2004). Litter cover was calculated as the proportion of hits where litter was recorded as a canopy layer. We calculated the amount of bare ground as the proportion of hits where the ground surface was recorded as bare soil or rock with no canopy layers overhead. Total ground cover was calculated as the proportion of pin drops where any plant canopy was encountered. At each site, measurements from all transects were averaged to create site-level estimates.

The ocular protocol consisted of qualitative, ocular estimates of cover within five 1 m² plot frames separated by 5 m along a single transect (Figure 1). The transect was oriented at 180° from the plot centre. For each plot frame, cover of all vegetation and soil components was estimated from an overhead perspective in 5% increments so that the sum of all components in the frame totalled 100% (Homer et al. 2012). Shrubs and trees were estimated to the species level except for sagebrush, which was estimated to the subspecies level. Herbaceous vegetation was estimated for the categories of perennial grasses, annual grasses, and forbs. Estimates of litter were the combined cover of dead

standing woody vegetation, detached plants, and animal matter. Bare ground estimates included exposed soil and rocks. Cover estimates within each plot frame were averaged together to obtain site-level estimates.

3.4. Statistical analyses

Statistical analyses followed two main steps. We first conducted limits of agreement analysis to examine the degree of correspondence between quantitative and ocular estimates of cover. We then used beta-distribution regression to quantify the relationships between quantitative and ocular-protocol estimates and between the field estimates and the RapidEye imagery. All statistical analyses were performed in R version 2.15 (<http://www.r-project.org>, accessed 4 October 2012). The *betareg* package developed by Cribari-Neto and Zeileis (2010) was used for the beta-distribution regression analysis.

Because of limited sample sizes within strata, we evaluated whether we could pool observations across strata by comparing differences between the quantitative and ocular methods by stratum. If the differences between methods were consistent across strata, we could assume that similar double-sampling regression equations would be derived for those strata. To test this, we performed a one-way analysis of variance (ANOVA) on the differences between the quantitative and ocular method by stratum for each indicator listed in Table 2. The ANOVAs were followed up with two-way multiple comparison tests using the Tukey–Kramer method to control for family-wise Type I error rate (Bretz, Hothorn, and Westfall 2010). The riparian and aspen strata were found to be significantly different (at the $\alpha = 0.05$ level) than the other strata for multiple indicators. No consistent differences were found among the other strata. Consequently, we excluded the aspen and riparian strata (because there were not enough sample points to consider them separately) and pooled the remaining data.

3.4.1. Limits of agreement

Two-phase sampling requires only that the first- and second-phase measurements be correlated, but the degree of that correlation determines whether or not two-phase sampling will be more efficient than sampling a single phase (Lohr 2009). In this study, however, our first and second phases were measurements of the same indicators using different methods. In this case, it is necessary to ask not only how well the measures are correlated, but also how well they agree with each other. A measure of agreement informs on the average bias and precision of the techniques relative to each other for estimating vegetation cover.

If true values of a parameter are known for a set of sample units, the accuracy and precision of a method for measuring that parameter can be calculated as deviation from this ‘gold standard’. In this case, when comparing alternative measurement methods against a known parameter, the most accurate and precise method is easy to determine. Comparison of two different methods that measure the same unknown parameter is difficult, however, if there is no way to establish the true value of the quantity being measured (Bland and Altman 1999).

The correlation between two measures of a common parameter for a set of sample units is typically used as a measure of agreement between two methods (Bland and Altman 2003). However, this approach is flawed because two methods that measure the same parameter should be expected to have a high correlation to each other even if there is systematic bias between the two methods or if one method is less precise than the other (Bland and Altman 1999). Strong correlation does not imply a high degree of agreement

Table 2. Relationships between quantitative and qualitative ocular estimates of ecosystem indicators.

Indicator	ρ	ρ_{rank}	Limits of agreement		Beta regression			
			Mean difference	Standard error	Pseudo- R^2	Intercept	β	φ
Tree cover	0.7959	0.8535	-0.0145	0.1913	0.6477	-1.7189	3.2189	12.477
Shrub cover	0.8596	0.8595	-0.0328	0.2470	0.7156	-1.4180	2.4497	12.247
Sagebrush cover	0.7249	0.8118	-0.0237	0.1828	0.5795	-1.7393	3.2380	13.226
Perennial grass cover	0.7169	0.7919	-0.0624	0.1140	0.5588	-1.9631	3.3439	38.400
Annual grass cover	0.0861	0.3391	-0.0040	0.0040	0.0400	-2.1897	3.1825	104.4
Bare ground	0.8339	0.8301	0.1746	0.3496	0.6065	-1.2049	1.9761	10.767
Total ground cover	0.0366	-0.0583	-0.5933	0.4424	—	—	—	—
Total ground cover*	0.7930	0.7376	0.0473	0.2606	0.5605	-0.8636	2.2330	9.119
Litter cover	0.1861	0.1482	-0.3625	0.4826	—	—	—	—
Litter cover†	0.4634	0.3564	0.1784	0.3231	0.2108	-0.9721	4.7370	6.420

Notes: *One minus the ocular-estimated bare ground was more strongly correlated to total cover estimated by the quantitative method. This suggests difficulty in making ocular estimates of overall cover at a plot level.

†Ocular estimates of litter cover were more strongly correlated to quantitative estimates of woody litter (diameter > 5 mm). This suggests that ocular estimates of litter favour larger litter and underrepresent fine litter.

between the methods where agreement is defined as the difference in measurement of the same parameter using two different methods.

Bland and Altman (1986) proposed limits of agreement as a better description of how well two different methods measure the same parameter. The limits of agreement estimate the mean difference, \bar{d} between the two methods (i.e. bias) and the standard deviation of the differences, s_d . If the differences are normally distributed, then 95% of the differences (LOA_{95}) will be $d \pm 1.96s_d$. The smaller \bar{d} and LOA_{95} are, the better the agreement between the two methods.

We calculated \bar{d} and LOA_{95} between the quantitative and ocular-protocol estimates for each indicator. The observed \bar{d} for each indicator followed a normal distribution assessed using the Wilk–Shapiro test (Royston 1982). Differences between the two methods for each sample plot were plotted against the average plot value from the two methods (see Bland and Altman 1999). We also calculated linear correlation and rank (i.e. ‘Spearman’) correlation between the quantitative and ocular estimates for each indicator.

3.4.2. Beta-distribution regression

Vegetation cover data (expressed as percentages or proportions) often do not conform to assumptions of standard linear regression methods because cover values have a limited range [0,1], are often not normally distributed (and cannot be easily transformed to make them so), and exhibit variances that are not consistent across the range of values (i.e. variance approaches zero at the limits) (Damgaard 2009; Espinheira, Ferrari, and Cribari-Neto 2008).

An alternative for analysing and modelling cover data is regression based on a beta distribution (i.e. beta regression, Brehm and Gates 1993). Chen et al. (2006) showed that plant cover data often follow a beta distribution. Damgaard (2009) suggested that analyses of continuous plant cover data based on the beta distribution were preferable to standard statistical techniques. Korhonen et al. (2007), Eskelson et al. (2011), and Chen et al. (2008) used beta regression for estimating plant cover.

Beta regression has several properties that make it useful for analysing plant cover data. First, the beta distribution is bounded by 0 and 1 and beta regression assumes only that the dependent variable is continuous, interval-level, and bounded between two known endpoints (Smithson and Verkuilen 2006).

Second, beta regression allows changes in variance to be modelled explicitly and separately from the mean (Smithson and Verkuilen 2006). The beta distribution $\beta(\mu, \phi)$ has the density function

$$f(y; \mu, \phi) = \frac{\Gamma(\phi)}{\Gamma(\mu\phi)\Gamma((1-\mu)\phi)} y^{\mu\phi-1} (1-y)^{(1-\mu)\phi-1}, y \in (0, 1), \quad (1)$$

where $\Gamma(\cdot)$ is the gamma function (Ospina and Ferrari 2012). Two parameters of beta distribution are μ (mean) and ϕ (precision parameter). Precision is related to, but different to variance because for bounded distributions, variance and mean are related (Smithson and Verkuilen 2006) by:

$$\sigma^2 = \frac{\mu(1-\mu)}{(1+\phi)}. \quad (2)$$

Considering precision rather than variance allows for precision to be modelled independently from the mean (Smithson and Verkuilen 2006). Thus, for a fixed value of μ , the larger the value of ϕ , the smaller the variance of y (Ospina and Ferrari 2012). If y is $B(\mu, \phi)$, then $E(y) = \mu$ and $\text{Var}(y) = \mu(1-\mu)/(\phi+1)$ (Ospina and Ferrari 2012).

Third, because the beta distribution can take on many different shapes, beta regression does not require proportion data to be transformed even if the data are highly skewed (Espinheira, Ferrari, and Cribari-Neto 2008). In the original formulation of beta distribution, two parameters, ω and τ , act as shape parameters that pull the density towards 0 and 1, respectively (Smithson and Verkuilen 2006). By varying the shape parameters, the beta distribution can accommodate different shapes of data distribution such as 'J', 'L', 'one-peak', 'U', or rectangular (Chen et al. 2006; Eskelson et al. 2011) – allowing the beta distribution to be fit to a wide range of cover datasets without the need for transformations.

We used beta-distribution regression with the ocular-protocol estimates as the independent variable and the quantitative protocol estimates as dependent variable to develop a linear model that described the relationship between indicator values from the two methods. Beta regression does not produce a true R^2 value, but we used the correlation between the observations, to which a log-link function (e.g. PROBIT function in this study) had been applied, and the model predictions (i.e. a pseudo R^2) as measures of explained variation (see Ferrari and Cribari-Neto 2004; Smithson and Verkuilen 2006). We then applied the regression parameters (linear regression model slope and intercept) to the ocular estimates to produce 'corrected' ocular estimates (i.e. predictions of quantitative method estimates). We then used beta regression a second time to compare the quantitative protocol, ocular protocol, and corrected ocular estimates to the RapidEye imagery for each indicator, using the pseudo R^2 values to determine strength of the relationships.

One shortcoming of the beta distribution is that it is not suitable for modelling datasets that contain observations with values of zero or one (Ospina and Ferrari 2012), because the logits of these extreme values are undefined. Because our datasets had very few observations with a value of zero and none with a value of one, we followed the recommendation of Smithson and Verkuilen (2006) to shrink the interval range of each variable to [0.005 to 0.995]. As long as the data are not zero- or one-inflated, this approach introduces a trivial amount of bias. In cases of zero- or one-inflation, a multi-stage procedure that models extreme values as separate, larger-scale processes from the continuous data is preferable (Damgaard 2009).

4. Results

Correlations between the quantitative- and ocular-protocol estimates were variable (Table 2). Indicators for dominant site components (i.e. tree, shrub, sagebrush, and perennial grass cover, bare ground) had parametric and rank correlations greater than 0.7. Annual grass cover estimates from the ocular and quantitative protocols were poorly correlated ($\rho = 0.0366$) but there were relatively few sites where more than a trace amount of annual grasses was recorded ($n = 9$ for ocular protocol, $n = 14$ for quantitative protocol). Ocular estimates of total ground cover were poorly correlated with quantitative protocol estimates of ground cover ($\rho = 0.0366$). A derived ocular estimate of total ground cover (one minus the estimated bare ground) yielded a much higher correlation to quantitative-protocol total ground cover ($\rho = 0.7930$). Ocular estimates of litter cover were more strongly correlated to quantitative-protocol estimates of woody litter cover ($\rho = 0.4634$) rather than total litter cover ($\rho = 0.1861$). Given that the derived indicators

for total ground cover and litter performed better than their direct ocular estimates, all subsequent results report the derived values for these two indicators.

The limits of agreement analysis showed that in all cases, ocular estimates of vegetation cover were lower than corresponding quantitative protocol estimates (Table 2, Figure 2). For dominant vegetation indicators, average underestimates were between 1.45% (tree cover) and 6.24% (perennial grass cover). Annual grass cover was underestimated the least, but also occurred with low cover at the few sites where it was recorded. The ocular protocol tended, on average, to overestimate bare ground by over 17%. The derived ocular estimates of total ground cover and litter cover tended to overestimate compared with the AIM protocol by 3.26% and 18.19%, respectively.

For bare ground, derived total canopy cover (which was related to quantitative-protocol bare ground measurements), and litter cover, there were apparent trends in the difference between quantitative and ocular-protocol estimates with increasing average cover (Figure 2). Ocular estimates of bare ground became higher than quantitative estimates as the amount of bare ground increased. The opposite pattern occurred for the total canopy cover. This trend in difference did not manifest in the derived total canopy cover indicator, however, suggesting non-stationarity in the ocular estimates for canopy cover and bare ground. Litter cover and derived litter cover also showed trends in difference with increasing cover.

Width of the LOA₉₅ was also variable by indicator (Table 2, Figure 2). For vegetation indicators, LOA₉₅ was between 11.4% and 24.7% perennial grass cover and shrub cover, respectively. The LOA₉₅ for bare ground (35.0%) and the derived ocular-estimate variables, total ground cover (26.0%), and litter cover (32.3%) were the highest.

Results of beta regression between the quantitative and ocular-protocol estimates followed the correlation and LOA results (Table 2, Figure 3). Pseudo- R^2 values were lower for all indicators than the normal parametric and rank correlations, which was expected (see Ferrari and Cribari-Neto 2004). Annual grass and litter had the lowest pseudo- R^2 values at 0.04 and 0.2108, respectively. All other indicators has pseudo- R^2 values greater than 0.5.

Relationships between the field-estimated indicators and the RapidEye imagery were also variable (Table 3). The quantitative protocol estimates yielded good beta-regression pseudo- R^2 values (>0.7) for all indicators except tree, sagebrush, and annual grass cover. Beta regression between ocular-protocol estimates and the RapidEye imagery gave lower-pseudo R^2 values for all indicators, with only three indicators (shrub cover, bare ground, and total canopy cover) exceeding 0.5. Corrected ocular estimates achieved higher pseudo- R^2 values than just the ocular estimates alone for all indicators except annual grass and litter cover – the two indicators with the poorest relationships between the quantitative and ocular-protocol estimates. The gain in pseudo- R^2 was modest for sagebrush and perennial grass cover. Corrected ocular estimates performed almost as well as the quantitative estimates for total ground cover and bare ground.

5. Discussion

Our results show that a double-sampling approach can be used to improve the relationship between ocular estimates and satellite imagery for some indicators. For indicators where there was a strong correlation between the two protocols, the corrected ocular estimates achieved nearly as good results as the quantitative protocol alone. This was generally the case for dominant site features (e.g. shrubs and bare ground). When the correlation between quantitative and ocular-protocol estimates was not as strong (e.g. for minor site components such as

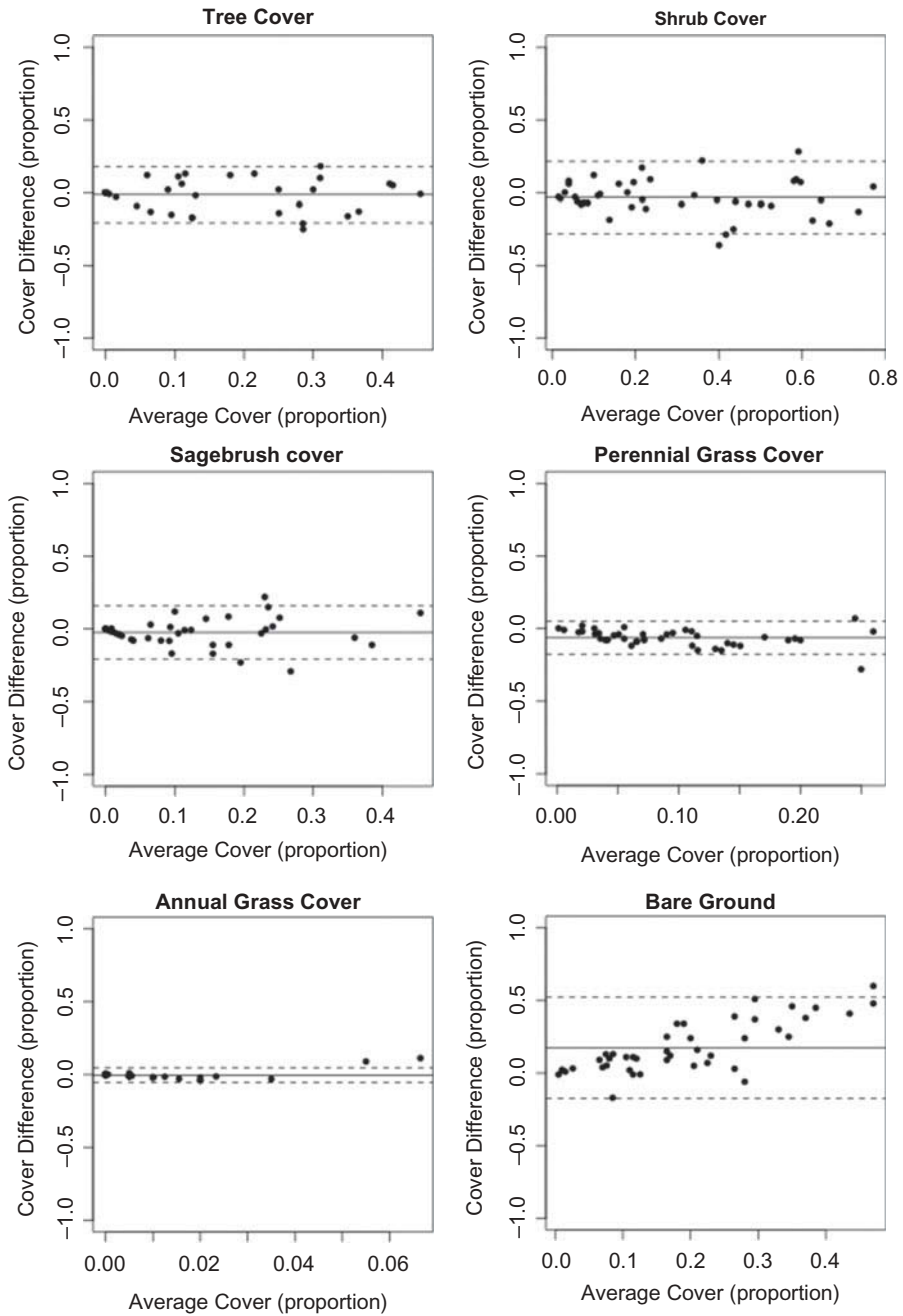


Figure 2. Limits of agreement show the degree of correspondence between two different methods of measuring the same indicator. Methods with a high degree of correspondence will have narrow confidence intervals. Bias between methods results in a mean difference (solid line) that is different to zero. Dashed lines are 95% confidence limits of difference between the two methods.

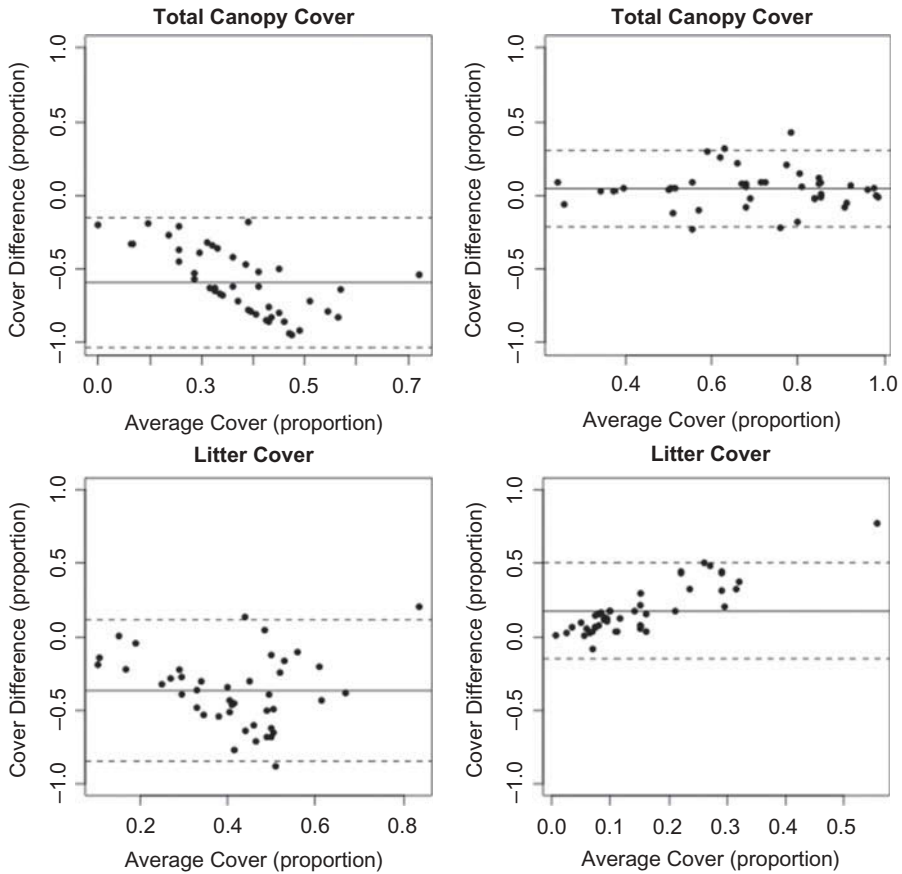


Figure 2. (Continued).

perennial grasses), there was still some advantage to double-sampling, but it was not as great. When the relationship between the two protocols was weak, correlations between the corrected ocular estimates and the RapidEye imagery could be unpredictable. In the case of annual grasses, corrected ocular estimates performed much better than either the quantitative or ocular-protocol estimates alone. For litter cover, though, corrected ocular estimates performed much worse than either the quantitative or ocular-protocol estimates. Both of these cases highlight poor model generalization as a result of low correlation between the two field protocols. This suggests that at some point the relationship between the two field techniques becomes sufficiently low that it is no longer advantageous to consider double-sampling.

Our results also pointed to several issues in the use of ocular estimation techniques. The differences in correlation between the ocular and quantitative protocol estimates by indicator suggest that observers could achieve reliable ocular estimates of cover only for dominant site features. Additionally, the poor correlation between ocular and quantitative protocol estimates for annual grasses and litter suggests that ocular estimation of cover is difficult for indicators with low amounts of cover. This could particularly be the case if the indicator being estimated is evenly distributed in the sample area. Also, the poor

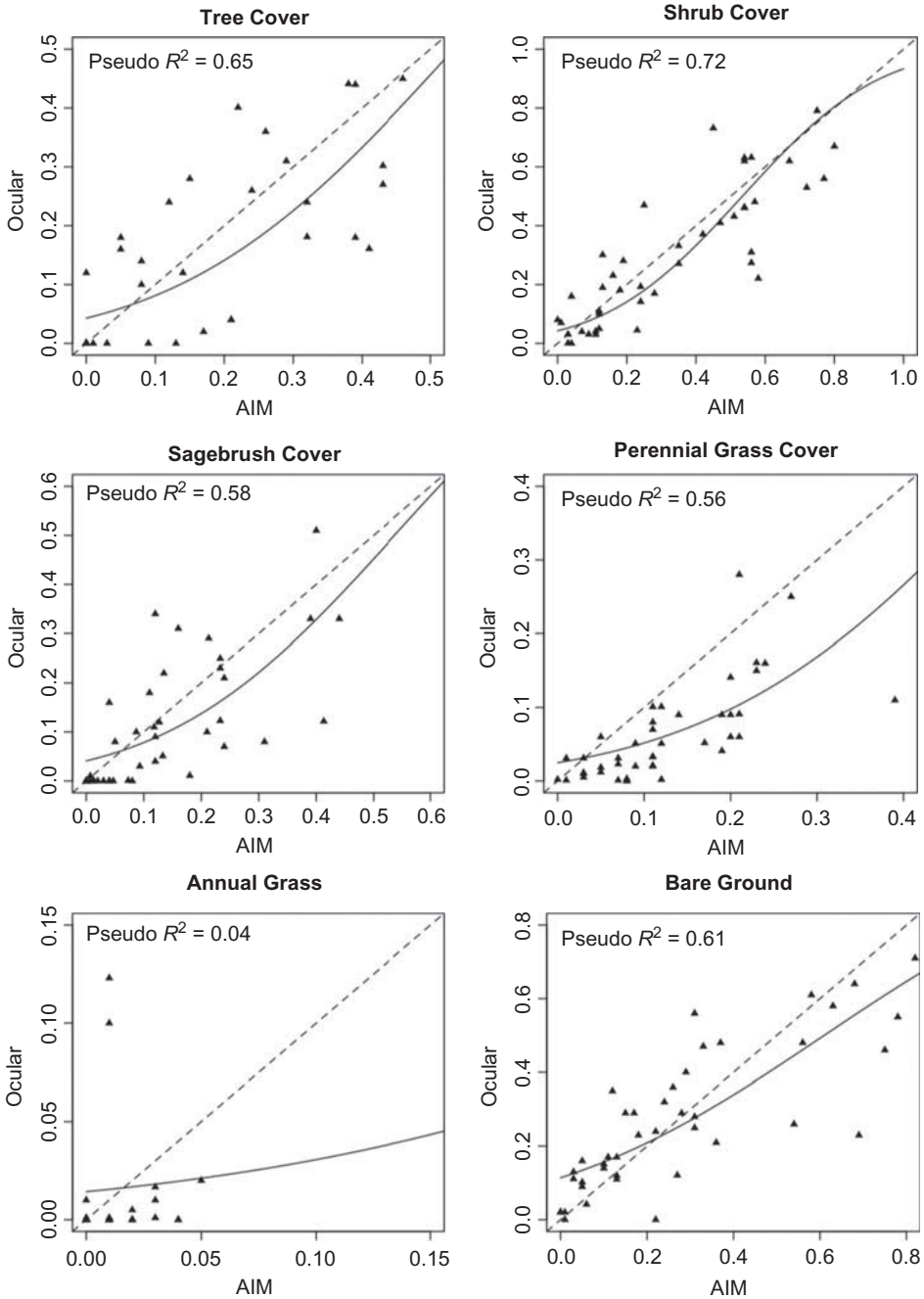


Figure 3. Scatter-plots of quantitative *versus* qualitative estimates of ecosystem indicators. Solid line is the beta-regression model. Dashed line is 1:1. Pseudo- R^2 values from the beta-regression model are from [Table 2](#).

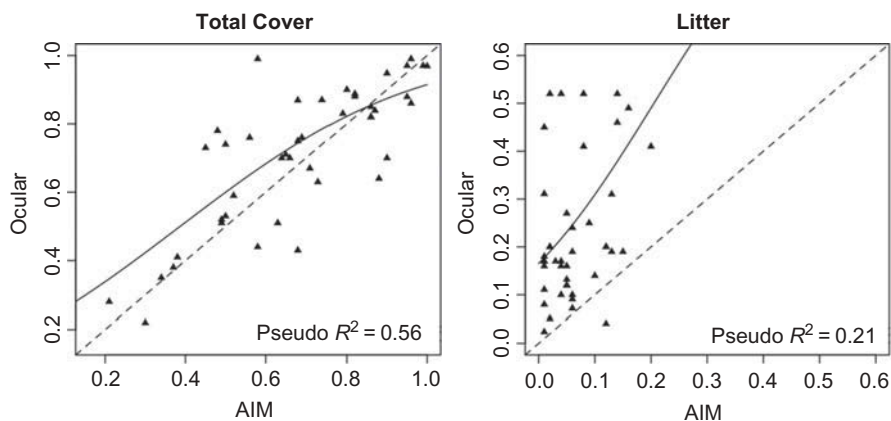


Figure 3. (Continued).

Table 3. Pseudo- R^2 values of beta regression between field estimates of ecosystem indicators and band values from RapidEye satellite imagery.

Indicator	Quantitative	Qualitative ocular estimates	Corrected qualitative
Tree cover	0.4342	0.3971	0.4134
Shrub cover	0.7851	0.6966	0.7788
Sagebrush	0.4669	0.4112	0.3945
Perennial grass cover	0.8513	0.3634	0.4415
Annual grass cover	0.3044	0.1888	0.3146
Bare ground	0.7881	0.6245	0.7680
Total ground cover	0.8702	0.6356	0.8638
Litter cover	0.7405	0.4227	0.2724

correlation between quantitative and ocular estimates of total canopy cover and litter strongly suggests that observers have difficulty estimating cover across multiple plant functional groups (e.g. cover of all vegetation grouped) or indicator types (e.g. woody and herbaceous litter grouped). This conclusion is supported by the lower correlation of ocular estimates of litter cover to quantitative protocol total litter cover *versus* woody litter cover. Observers were challenged to sum cover estimates across different classes (i.e. fine herbaceous litter and woody litter). Based on these results, we suggest that observers estimate only for single indicators at a time and only for dominant vegetation features.

The limits of agreement analysis was a helpful supplement to simple correlation and beta regression between the two protocols, but it was not sufficient for understanding how well the ocular protocol could substitute for the quantitative protocol. Mean difference and 95% limits of agreement adequately captured the deviation between the two techniques for most indicators, but presented artificially low values for indicators such as annual grasses. The limits of agreement analysis is based on the assumption that two techniques for measuring the same variable should be highly correlated (Bland and Altman 2003). While this held for many of the indicators we considered, it did not hold for annual grasses, litter, and total canopy cover – indicators for which the correlation between the measurement values from the two protocols was very low. In the case of annual grass, the limits of agreement gave misleadingly low results because the range of values of the indicator was small (i.e. annual grasses were either absent or low in cover).

Standardization of the average differences used in the limits of agreement analysis may be a better metric for detecting where low correlation exists between two measures with restricted value ranges.

We used beta regression in two parts of this study: (1) modelling the relationship between the quantitative and ocular-protocol estimates and correcting the ocular estimates and (2) determining the relationship between the field estimates and the RapidEye imagery. While useful to both parts of the study, different aspects of the beta distribution were advantageous in each context. Regression of site-level cover estimates (binomial variables) from the two protocols using the beta distribution allowed for the model to be bounded by 0 and 1 and, more importantly, for the variance to be modelled as a function of the mean. When comparing the site estimates to the RapidEye imagery, however, we were considering sets of proportions. In this case our cover estimates were a non-binomial, continuous variable that was bounded by 0 and 1. The beta distribution is an appropriate choice in this situation too because it is similarly bounded and can adapt to the shape of the data distribution without making *a priori* assumptions (e.g. assuming normality).

For some indicators we considered, there was a high proportion of sites where the indicator did not occur (e.g. sites with no sagebrush, annual grass). This poses two problems for double-sampling using beta regression. First, the beta distribution is not defined at zero, so we needed to add a small value to each indicator estimate. Second, the high rate of zeros may distort the shape of the distribution of the non-zero observations. A zero-inflated regression model (e.g. Ospina and Ferrari 2012) may produce better results in this case. In zero-inflated regression, the presence or absence of the indicator is modelled first, and then the value or proportion modelled within the presence areas. This kind of approach may have yielded better results for indicators like annual grass cover.

When selecting methods for obtaining vegetation cover estimates in the field, it is important to consider not only the time required to make measurements at a site, but also the training requirements for obtaining reliable data. Training and calibration of field personnel for the LPI method used in the quantitative protocol typically takes only a day. The LPI method seeks to minimize subjective decisions by observers, so adherence to the protocol and the ability to identify plants are the minimum requirements for successful implementation (Herrick et al. 2009). For the ocular protocol, training time can be lengthy as observers learn what cover amounts look like under different conditions, and calibrating multiple observers to obtain consistent results can be challenging. Experience of observers can play a large role in the quality of ocular estimates of vegetation cover. Ocular estimation methods also require frequent recalibration throughout the season and whenever moving to a new vegetation type to maintain consistent results.

Additional research is needed on what factors affect the reliability of indicator estimates using ocular techniques in different environments. However, as aerial photography becomes more widely available through platforms such as unmanned aerial systems (Laliberte, Winters, and Rango 2011; Rango and Laliberte 2010; e.g. Rango et al. 2009), interpretation of very high-resolution imagery (Booth and Cox 2008) may be a better and more efficient means of rapidly collecting training data for remote sensing that could be corrected via double-sampling (Karl et al. 2012).

6. Conclusion

Double-sampling can be a valuable technique for balancing the need for large sample sizes (and thus rapid field techniques) with quantitative rigour in field measurements. The

advantage of double-sampling is that it can improve the relationship of rapidly collected qualitative measurements to imagery. However, there is some cost associated with implementing a double-sampling approach to training remote-sensing projects due to the need to collect both qualitative and quantitative data at some locations. This additional cost needs to be weighed against the expected benefits of double-sampling. Increasingly, though, these costs can be offset (at least to some degree) by leveraging quantitative data collected as part of ongoing field-based monitoring programmes.

As a means of improving training data for remote-sensing projects, however, double-sampling should only be used where there is a strong correlation between measurement values of the quantitative and qualitative methods. Accordingly, ocular techniques should be used only when they can generate reliable estimates of cover (e.g. dominant site features, for a single life form or indicator type). Multiple metrics (e.g. correlation and limits of agreement) and appropriate statistical distributions (e.g. beta distribution for proportion or bounded variables) should be used to assess and model the relationship between the two techniques being evaluated.

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References

- Ahmed, J., C. D. Bonham, and W. A. Laycock. 1983. "Comparison of Techniques Used for Adjusting Biomass Estimates by Double Sampling." *Journal of Range Management* 36: 217–221.
- Andujar, D., A. Ribeiro, R. Carmona, C. Fernandez-Quintanilla, and J. Dorado. 2010. "An Assessment of the Accuracy and Consistency of Human Perception of Weed Cover." *Weed Research* 50 (6): 638–647. doi:10.1111/j.1365-3180.2010.00809.x.
- Bart, J., S. Earnst, and M. Murphy. 2002. "Double Sampling to Estimate Density and Population Trends in Birds." *The Auk* 119 (1): 36–45.
- Bergstedt, J., L. Westerberg, and P. Milberg. 2009. "In the Eye of the Beholder: Bias and Stochastic Variation in Cover Estimates." *Plant Ecology* 204: 271–283.
- Bland, J. M., and D. G. Altman. 1986. "Statistical Methods for Assessing Agreement Between Two Methods of Clinical Measurement." *The Lancet* 327 (8476): 307–310. doi:http://dx.doi.org/10.1016/S0140-6736(86)90837-8.
- Bland, J. M., and D. G. Altman. 1999. "Measuring Agreement in Method Comparison Studies." *Statistical Methods in Medical Research* 8 (2): 135–160. doi:10.1177/096228029900800204.
- Bland, J. M., and D. G. Altman. 2003. "Applying the Right Statistics: Analyses of Measurement Studies." *Ultrasound in Obstetrics and Gynecology* 22: 85–93.
- Blaschke, T., M. Conradi, and S. Lang. 2002. "Multi-scale Image Analysis for Ecological Monitoring of Heterogeneous, Small Structured Landscapes." Paper presented at the Proceedings of SPIE, Toulouse, September 17, 2001.
- Booth, T. D., and S. E. Cox. 2008. "Image-Based Monitoring to Measure Ecological Change in Rangeland." *Frontiers of Ecology and the Environment* 6 (4): 185–190.
- Booth, T. D., S. E. Cox, T. W. Meikle, and C. Fitzgerald. 2006. "The Accuracy of Ground-Cover Measurements." *Rangeland Ecology and Management* 59: 179–188.
- Booth, T. D., D. Glenn, B. Keating, J. Nance, S. E. Cox, and J. P. Barriere. 2003. "Monitoring Rangeland Watersheds with Very-large Scale Aerial Imagery." Paper presented at the First Interagency Conference on Research in the Watersheds, Benson, AZ, October 27–30.
- Booth, T. D., and P. T. Tueller. 2003. "Rangeland Monitoring Using Remote Sensing." *Arid Land Research and Management* 17 (4): 455–467.

- Brehm, J., and S. Gates. 1993. "Donut Shops and Speed Traps: Evaluating Models of Supervision on Police Behavior." *American Journal of Political Science* 37: 555–581.
- Bretz, F., T. Hothorn, and P. Westfall. 2010. *Multiple Comparisons Using R*. Boca Raton, FL: CRC Press.
- Bureau of Land Management. 2012. *Draft Resource Management Plan Amendment and Environmental Impact Statement for Oil and Gas Development*. Denver, CO: White River Field Office, Bureau of Land Management.
- Chen, J., M. Shiyomi, C. Bonham, T. Yasuda, Y. Hori, and Y. Yamamura. 2008. "Plant Cover Estimation Based on the Beta Distribution in Grassland Vegetation." *Ecological Research* 23 (5): 813–819. doi:10.1007/s11284-007-0443-3.
- Chen, J., M. Shiyomi, Y. Yamamura, and Y. Hori. 2006. "Distribution Model and Spatial Variation of Cover in Grassland Vegetation." *Grassland Science* 52 (4): 167–173. doi:10.1111/j.1744-697X.2006.00065.x.
- Crawford, J. A., R. A. Olson, N. E. West, J. C. Mosley, M. A. Schroeder, T. D. Whitson, R. F. Miller, M. A. Gregg, and C. S. Boyd. 2004. "Ecology and Management of Sage-Grouse and Sage-Grouse Habitat." *Journal of Range Management* 57: 2–19.
- Cribari-Neto, F., and A. Zeileis. 2010. "Beta Regression in R." *Journal of Statistical Software* 34 (2): 1–24.
- Damgaard, C. 2009. "On the Distribution of Plant Abundance Data." *Ecological Informatics* 4: 76–82.
- Dethier, M. N., E. S. Graham, S. Cohen, and L. M. Tear. 1993. "Visual Versus Random-Point Percent Cover Estimations: 'Objective' Is Not Always Better." *Marine Ecology Progress Series* 96: 93–100.
- Duniway, M. C., J. W. Karl, S. Schrader, N. Baquera, and J. E. Herrick. 2011. "Rangeland and Pasture Monitoring: An Approach to Interpretation of High-Resolution Imagery Focused on Observer Calibration for Repeatability." *Environmental Monitoring and Assessment*. doi:10.1007/s10661-011-2224-2.
- Elzinga, C. L., D. W. Salzer, and J. W. Willoughby. 1998. *Measuring and Monitoring Plant Populations*. Denver, CO: US Department of the Interior, Bureau of Land Management, National Applied Resource Sciences Center.
- Eskelson, B. N. I., L. Madsen, J. C. Hagar, and H. Temesgen. 2011. "Estimating Riparian Understory Vegetation Cover with Beta Regression and Copula Models." *Forest Science* 57 (3): 212–221.
- Espinheira, P. L., S. L. P. Ferrari, and F. Cribari-Neto. 2008. "On Beta Regression Residuals." *Journal of Applied Statistics* 35 (4): 407–419. doi:10.1080/02664760701834931.
- Eva, H., and E. F. Lambin. 1998. "Remote Sensing of Biomass Burning in Tropical Regions: Sampling Issues and Multisensor Approach." *Remote Sensing of Environment* 64 (3): 292–315.
- Ferrari, S., and F. Cribari-Neto. 2004. "Beta Regression for Modelling Rates and Proportions." *Journal of Applied Statistics* 31 (7): 799–815.
- Floyd, D. A., and J. E. Anderson. 1987. "A Comparison of Three Methods for Estimating Plant Cover." *Journal of Ecology* 71 (1): 221–228.
- Hanley, T. A. 1978. "A Comparison of the Line-Interception and Quadrat Estimation Methods of Determining Shrub Canopy Coverage." *Journal of Range Management* 31 (1): 60–62.
- Herrick, J. E., J. W. Van Zee, K. M. Havstad, L. M. Burkett, and W. G. Whitford. 2009. *Monitoring Manual for Grassland, Shrubland, and Savanna Ecosystems*. Las Cruces, NM: USDA-ARS Jornada Experimental Range.
- Homer, C. G., C. L. Aldridge, D. K. Meyer, M. J. Coan, and Z. H. Bowen. 2008. *Multiscale Sagebrush Rangeland Habitat Modeling in Southwest Wyoming*. Reston, VA: US Geological Survey.
- Homer, C. G., C. L. Aldridge, D. K. Meyer, and S. J. Schell. 2012. "Multi-Scale Remote Sensing Sagebrush Characterization with Regression Trees over Wyoming, USA: Laying a Foundation for Monitoring." *International Journal of Applied Earth Observation and Geoinformation* 14 (1): 233–244.
- Hunt, E. R. Jr, J. H. Everitt, J. C. Ritchie, M. S. Moran, T. D. Booth, G. L. Anderson, P. E. Clark, and M. S. Seyfried. 2003. "Applications and Research Using Remote Sensing for Rangeland Management." *Photogrammetric Engineering and Remote Sensing* 69 (6): 675–693.
- Kalkhan, M. A., R. M. Reich, and T. J. Stohlgren. 1998. "Technical Note Assessing the Accuracy of Landsat Thematic Mapper Classification Using Double Sampling." *International Journal of Remote Sensing* 19 (11): 2049–2060. doi:10.1080/014311698214857.

- Karl, J. W. 2010. "Spatial Predictions of Cover Attributes of Rangeland Ecosystems Using Regression Kriging and Remote Sensing." *Rangeland Ecology and Management* 63 (3): 335–349. doi:10.2111/RED-D-09-00074.1.
- Karl, J. W., M. C. Duniway, S. M. Nusser, J. D. Opsomer, and R. S. Unnasch. 2012. "Using Very-Large Scale Aerial (VLSA) Imagery for Rangeland Monitoring and Assessment: Some Statistical Considerations." *Rangeland Ecology & Management* 65 (4): 330–339. doi:10.2111/rem-d-11-00102.1.
- Kennedy, K. A., and P. A. Addison. 1987. "Some Considerations for the Use of Visual Estimates of Plant Cover in Biomonitoring." *Journal of Ecology* 75: 151–157.
- Kennedy, R. E., P. A. Townsend, J. E. Gross, W. B. Cohen, P. Bolstad, Y. Q. Wang, and P. Adams. 2009. "Remote Sensing Change Detection Tools for Natural Resource Managers: Understanding Concepts and Tradeoffs in the Design of Landscape Monitoring Projects." *Remote Sensing of Environment* 113 (7): 1382–1396. doi:10.1016/j.rse.2008.07.018.
- Klimes, L. 2003. "Scale-Dependent Variation in Visual Estimates of Grassland Plant Cover." *Journal of Vegetation Science* 14: 815–821.
- Knick, S. T., J. T. Rotenberry, and T. J. Zarriello. 1997. "Supervised Classification of Landsat Thematic Mapper Imagery in a Semi-Arid Rangeland by Nonparametric Discriminant Analysis." *Photogrammetric Engineering and Remote Sensing* 63 (1): 79–86.
- Köhl, M., S. S. Magnussen, and M. Marchetti. 2006. *Sampling Methods, Remote Sensing and GIS Multiresource Forest Inventory*. Berlin: Springer-Verlag.
- Korhonen, L., K. T. Korhonen, M. Rautiainen, and P. Stenberg. 2006. "Estimation of Forest Canopy Cover: A Comparison of Field Measurement Techniques." *Silva Fennica* 40 (4): 577.
- Korhonen, L., K. T. Korhonen, P. Stenberg, M. Maltamo, and M. Rautiainen. 2007. "Local Models for Forest Canopy Cover with Beta Regression." *Silva Fennica* 41 (4): 671–685.
- Laliberte, A. S., J. E. Herrick, A. Rango, and C. Winters. 2010. "Acquisition, Orthorectification, and Object-Based Classification of Unmanned Aerial Vehicle (UAV) Imagery for Rangeland Monitoring." *Photogrammetric Engineering and Remote Sensing* 76 (6): 661–672.
- Laliberte, A. S., C. Winters, and A. Rango. 2011. "UAS Remote Sensing Missions for Rangeland Applications." *Geocarto International* 26 (2): 141–156. doi:10.1080/10106049.2010.534557.
- Lohr, S. L. 2009. *Sampling: Design and Analysis*. 2nd ed. Boston, MA: Brooks/Cole, Cengage Learning.
- Mackinnon, W. C., J. W. Karl, G. R. Toevs, J. J. Taylor, M. S. Karl, C. S. Spurrier, and J. E. Herrick. 2011. *BLM Core Terrestrial Indicators and Methods*. Denver, CO: US Department of the Interior, Bureau of Land Management, National Operations Center.
- Marsett, R. C., J. Qi, P. Heilman, S. H. Beidenbender, M. C. Watson, S. Amer, M. Weltz, D. Goodrich, and R. Marsett. 2006. "Remote Sensing for Grassland Management in the Arid Southwest." *Rangeland Ecology and Management* 59: 530–540.
- Maxwell, E. L. 1976. "A Remote Rangeland Analysis System." *Journal of Range Management* 29: 66–73.
- McCoy, R. M. 2005. *Field Methods in Remote Sensing*. New York: Guilford Press.
- Neeser, C., A. R. Martin, P. Juroszek, and D. A. Mortensen. 2000. "A Comparison of Visual and Photographic Estimates of Weed Biomass and Weed Control." *Weed Technology* 14: 586–590.
- Ospina, R., and S. L. P. Ferrari. 2012. "A General Class of Zero-or-One Inflated Beta Regression Models." *Computational Statistics & Data Analysis* 56 (6): 1609–1623. doi:10.1016/j.csda.2011.10.005.
- Parker, R. C., and D. L. Evans. 2004. "An Application of LiDAR in a Double-Sample Forest Inventory." *Western Journal of Applied Forestry* 19 (2): 95–101.
- Pellant, M., P. Shaver, and K. Spaeth. 1999. "Field Test of a Prototype Rangeland Inventory Procedure in the Western USA." Paper presented at the Proceedings of the VI International Rangeland Congress, People and Rangelands, Building the Future, Townsville, July 19–23.
- Petersen, S. L., T. K. Stringham, and B. A. Roundy. 2009. "A Process-Based Application of State-and-Transition Models: A Case Study of Western Juniper (*Juniperus Occidentalis*) Encroachment." *Rangeland Ecology and Management* 62: 186–192.
- Qi, J., A. Chehbouni, A. R. Huete, Y. H. Kerr, and S. Sorooshian. 1994. "A Modified Soil Adjusted Vegetation Index." *Remote Sensing of the Environment* 30: 1311–1319.
- Rango, A., and A. S. Laliberte. 2010. "Impact of Flight Regulations on Effective Use of Unmanned Aircraft Systems for Natural Resource Applications." *Journal of Applied Remote Sensing* 4: 043539.

- Rango, A., A. S. Laliberte, J. E. Herrick, C. Winters, K. M. Havstad, C. Steele, and D. Browning. 2009. "Unmanned Aerial Vehicle Based Remote Sensing for Rangeland Assessment, Monitoring and Management." *Journal of Applied Remote Sensing* 2: 033542.
- Reeves, M. C., M. Zhao, and S. W. Running. 2006. "Applying Improved Estimates of MODIS Productivity to Characterize Grassland Vegetation Dynamics." *Rangeland Ecology and Management* 59 (1): 1–10.
- Royston, J. P. 1982. "An Extension of Shapiro and Wilk's W Test for Normality to Large Samples." *Applied Statistics* 31 (2): 115–124.
- Running, S. W., R. R. Nemani, F. A. Heinsch, M. Zhao, M. C. Reeves, and H. Hashimoto. 2004. "A Continuous Satellite-Derived Measure of Global Terrestrial Primary Production." *BioScience* 54 (6): 547–560.
- Seefeldt, S. S., and T. D. Booth. 2006. "Measuring Plant Cover in Sagebrush Steppe Rangelands: A Comparison of Methods." *Environmental Management* 37 (5): 703–711.
- Smithson, M., and J. Verkuilen. 2006. "A Better Lemon Squeezer? Maximum-Likelihood Regression with Beta-Distributed Dependent Variables." *Psychological Methods* 11 (1): 54–71. doi:10.1037/1082-989X.11.1.54.
- Soil Survey Staff. 2008a. *Soil Survey Geographic (SSURGO) Database for Douglas-Plateau Area, Colorado, Parts of Garfield and Mesa Counties*. Washington, DC: Natural Resources Conservation Service, US Department of Agriculture.
- Soil Survey Staff. 2008b. *Soil Survey Geographic (SSURGO) Database for Rifle area, Colorado, Parts of Garfield and Mesa Counties*. Washington, DC: Natural Resources Conservation Service, US Department of Agriculture.
- Soil Survey Staff. 2008c. *Soil Survey Geographic (SSURGO) Database for Rio Blanco County Area, Colorado*. Washington, DC: Natural Resources Conservation Service, US Department of Agriculture.
- Stehman, S. V. 1996. "Use of Auxiliary Data to Improve the Precision of Estimators of Thematic Map Accuracy." *Remote Sensing of Environment* 58 (2): 169–176. doi:http://dx.doi.org/10.1016/S0034-4257(96)00034-X.
- Stohlgren, T. J., K. A. Bull, and Y. Otsuki. 1998. "Comparison of Rangeland Vegetation Sampling Techniques in the Central Grasslands." *Journal of Range Management* 51 (2): 164–172.
- Taylor, J. O. 1987. *Oil Shale, Water Resources, and Valuable Minerals of the Piceance Basin, Colorado: The Challenge and Choices of Development*, 143 p. Washington, DC: United States Geological Survey Professional Paper 1310.
- Theobald, D. M., D. L. Stevens Jr, D. White, N. S. Urquhart, A. R. Olsen, and J. B. Norman. 2007. "Using GIS to Generate Spatially Balanced Random Survey Designs for Natural Resource Applications." *Environmental Management* 40: 134–146.
- Thompson, S. K. 2002. *Sampling*. 2nd ed. New York: John Wiley & Sons.
- Treitz, P. M., P. J. Howarth, R. C. Suffling, and P. Smith. 1992. "Application of Detailed Ground Information to Vegetation Mapping with High Spatial Resolution Digital Imagery." *Remote Sensing of Environment* 42 (1): 65–82. doi:10.1016/0034-4257(92)90068-U.
- USDA Natural Resources Conservation Service. 2003. *Soil Survey of Douglas-Plateau Area, Colorado, Parts of Garfield and Mesa Counties*, 356. Washington, DC: USDA Natural Resources Conservation Service.
- USDA Soil Conservation Service. 1982. *Soil Survey of Rio Blanco County Area, Colorado*, 164. Washington, DC: USDA Soil Conservation Service.
- USDA Soil Conservation Service. 1985. *Soil Survey of Rifle Area, Colorado*, 161. Washington, DC: USDA Soil Conservation Service.
- Washington-Allen, R. A., N. E. West, R. D. Ramsey, and R. A. Efroymson. 2006. "A Protocol for Retrospective Remote Sensing-Based Ecological Monitoring of Rangelands." *Rangeland Ecology and Management* 59: 19–29.
- Weber, K. T. 2006. "Challenges of Integrating Geospatial Technologies into Rangeland Research and Management." *Rangeland Ecology and Management* 59 (1): 38–43.
- Wylie, B. K., S. P. Boyte, and D. J. Major. 2012. "Ecosystem Performance Monitoring of Rangelands by Integrating Modeling and Remote Sensing." *Rangeland Ecology & Management*. doi:10.2111/rem-d-11-00058.1.
- Wylie, B. K., J. A. Harrington, S. D. Prince, and I. Denda. 1991. "Satellite and Ground-Based Pasture Production Assessment in Niger: 1986–1988." *International Journal of Remote Sensing* 12 (6): 1281–1300. doi:10.1080/01431169108929726.