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Characterizing rangeland vegetation using Landsat and 1-mm VLSA data in central Wyoming (USA)

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Abstract As an alternative to ground-cover data collection by conventional and expensive sampling techniques, we compared measurements obtained from very large scale aerial (VLSA) imagery for calibrating moderate resolution Landsat data. Using a grid-based sampling scheme, 162 VLSA images were acquired at 100 m above ground level. The percent vegetation cover in each photo was derived using SamplePoint (a manual inventory method) and VegMeasure (a reflectance based, automated method). Approximately two-thirds of the VLSA images were used for calibrating Landsat data while the remainder was used for validation. Regression models with Landsat bands accounted for 55% of the VegMeasure-based measurements of vegetation, whereas models that included both Landsat bands and elevation data accounted for 67%. The relationship between the Landsat bands and the percent vegetation cover measured by SamplePoint was lower ($R^2 = 20\%$), highlighting the differences between the inventory and reflectance based protocols. Results from the model validation indicated that the model's predictive power was lower when the vegetation cover was either <20% or >55%. Additional work is needed in these ecosystems to improve the calibration techniques for sites with low and high vegetation cover; however, these results demonstrate the VLSA imagery could be used for calibrating Landsat data and deriving rangeland vegetation cover. By adopting such methodologies the US Federal land management agencies can increase the efficiency of the monitoring programs in Wyoming and in other western states of the US.

Keywords Shrub land · Sagebrush · Remote sensing · Satellite data · Regression analysis

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Introduction

Rangelands are characterized by grass, forb, and shrub vegetation (e.g., the Sonoran desert, the sagebrush (*Artemesia* spp.) steppe, tall- and short-grass prairies). In the US, rangelands occupy 324 M ha, providing numerous ecological services of which grazing, wildlife habitat (including habitat for several species listed as threatened under the Federal Endangered Species Act (NS-GCT 2004; FWS 2005)), watersheds, recreation, and extractable minerals are commonly recognized. Less obvious are the rangeland biophysical processes important to a well-functioning global environment. Natural and human-induced rangeland disturbances such as wildfires, droughts, cattle grazing, and housing developments all influence rangeland vegetation and, in turn, affect the carbon and water cycles (Kolb and Sperry 1999; Gilmanov et al. 2004; Morgan et al. 2004). Given their ecological and economic importance, and increasing multiple uses, accurate and continuous assessment of rangeland is fundamental to ongoing sustainable use. Public US rangeland is primarily managed by the Department of Interior's Bureau of Land Management (BLM) and the Department of Agriculture's Forest Service (USFS). These agencies operate under several public laws including the Resources Planning Act (1974), Federal Land Policy and Management Act (1976), Soil and Water Resources Conservation Act (1977), Forest and Rangeland Resources Planning Act (1978), and the Environmental Monitoring and Assessment Act (1988). Included in each of these acts is the directive to monitor and account for the ecological "health" of the resources for which they are responsible.

The difficulties associated with statistically-adequate ecological assessments make conventional field survey and sampling impractical if not impossible to apply to the vast US rangelands (West 1999; Schino et al. 2003), and do not provide timely information for those regions that undergo frequent changes. Remote sensing provides a viable method for monitoring and characterizing rangeland vegetation. Moderate spatial resolution data collected by Landsat and other satellites provide a temporal resolution and economy not matched by aerial or ground methods. Several studies have demonstrated the utility of Landsat data for mapping rangeland vegetation (Todd et al. 1998; Ikeda et al. 1999; Hostert et al. 2003; Schino et al. 2003; Cingolani et al. 2004). Todd et al. (1998) found that Landsat bands were able to account for 67% of the variance in the measured biomass in grazed rangelands of Colorado (USA). However, most of the studies used correlation to analyze the relationship between field-measured vegetation data and remotely sensed reflectance values, and fewer studies have tested the relationship with regression models. Ancillary data such as elevation, slope, aspect, and soil type are often used together with the reflectance values recorded by Landsat to assist classification (Kozar et al. 2002; Zambon et al. 2006). For example, the association between elevation and species distribution was used to separate mountain fir (elevation range 2652–2774 m) from spruce-fir (elevation > 2774 m), though their spectral reflectance values were identical (Homer et al. 1997).

Precise ground-based measurements are required to calibrate the Landsat pixels prior to characterizing the rangeland vegetation. However, conventional ground-based methods of collecting calibration data are expensive. Seefeldt and Booth (2006) have demonstrated the utility of aerial images for monitoring and measuring rangeland ground cover using Very Large Scale Aerial (VLSA) photography. VLSA photography refers to low-altitude, high-resolution (1–20 mm GSD) imagery that is acquired intermittently during an aerial rangeland survey (Booth and Cox 2006). Booth et al. (2005a) reported that a sub-millimeter contact area had the highest correlation of measured cover to known values. VLSA surveys are excellent for acquiring large sample numbers, but they are a sampling, not a mapping method.

The goal of this study was to assess the potential of VLSA data (spatial resolution 1 mm) for calibrating Landsat Thematic Mapper 5 (TM5) data (spatial resolution 30 m) so as to extend the reach of highly detailed imaging with the field-of-view and periodicity of space imagery. Specific objectives of this study were: (1) Test the relationship between ground cover measurements derived from VLSA photos and Landsat reflectance values through regression analyses; (2) Compare the advantages of using transformed bands instead of raw Landsat reflectance values; and (3) Assess the value of incorporating the physiographic variables (elevation, slope and aspect) in the regression models. We used approximately two thirds of the VLSA data for testing the relationship and model development between the percent vegetation derived from VLSA and Landsat reflectance values. The rest of the data was used to test regression model validity. If a useful relationship exists, then a multi-scale approach that combines VLSA images and early growing season medium resolution satellite data could be used for some routine monitoring and for mapping rangeland plant communities.

Materials and methods

Study area

The 9,000-ha Hay Press Creek Pasture is in the northeast part of the Green Mountain Common Allotment, southwest of Jeffrey City, Wyoming (42°27′ N, 107°55′ W) between Green Mountain and the flood plain of the Sweetwater River (Fig. 1). It is managed by the US Department of the Interior, Bureau of Land Management, Lander Field Office. The pasture contains 85% sagebrush/grassland (*Artemisia tridentata* Nutt. ssp. *wyomingensis* Beetle and Young) (7,526 ha), 12% riparian area (1,096 ha), 2% Playa (161 ha) and 0.5% road (30 ha) (Beetle 1960; Booth et al. unpublished data).

Very large scale aerial photography (VLSA)

We acquired 162 color digital aerial images on 8th and 9th June 2004, using a light airplane (225-kg empty weight, fixed wing, three-axis), a navigation and camera-triggering system, a digital camera, and a laser rangefinder (Booth and Cox 2006). The aircraft speed ranged between 68 and 95 km/h. The navigation system was powered by Tracker software (Track'Air B.V., Oldenzaal, The Netherlands) on a laptop computer interfaced with (1) a central navigation box, (2) a differentially-corrected geographic positioning system and (3) a 15-cm in-cockpit pilot display. The navigation system was programmed using a laptop PC to automatically trigger the camera at 800-m intervals along 12 flight lines. We used a Canon EOS 1Ds 11.1-megapixel single lens reflex, color (RGB) digital camera with a Canon 600 mm f/4.0 EF lens plus a 1.4× teleconverter to yield the equivalent of a 840 mm, f/5.6 lens. (Canon USA, Lake Success, NY, USA). Shutter speed was manually set for 1/4,000th second with safety shift enabled to allow the shutter speed to slow in inadequate light. The camera was interfaced with a laptop PC (3.2-GHz, 40-GB-hard drive) running Canon Remote Capture software and images were stored directly on the hard drive. Images were initially saved as RAW (10MB compressed) files and later converted to 24-bit, 31 MB, 4064 × 2704-pixel TIFF files for analysis. A Riegl 3100VHS laser rangefinder (Riegl, Orlando, FL, USA) was used as an altimeter in conjunction with LaserLOG software (Booth et al. 2006a) to continuously read and record the airplane's altitude above-ground-level (AGL) below 300 m. Altitude was displayed for the pilot on the screen of the laptop storing the images, while stored data were saved for later correlation with images. Planned flight altitude for the upland survey was 100 m AGL with an expected image resolution of 1 mm ground surface distance (GSD) and a 3 × 4 m field of view. The flight plan of 12 E-W flight lines totaling 121 km was created by extracting coordinates of user-defined points drawn on a digital raster graphic in ArcView GIS 3.3 (ESRI, Redlands, CA), then using Track'Air SnapXYZ flight planning software to enter the coordinates into a flight plan utilized in flight by Track'Air SnapShot software. Photo targets were planned on a 0.8-km grid covering the entire pasture. A DGPS Max differentially-corrected global positioning system (DGPS) unit (CSI Wireless, Calgary, Alberta) with sub-meter accuracy was used to guide the pilot to the photo targets. Booth and Cox (2006) estimated that the cost of acquiring VLSA images was approximately $0.08 per hectare, based on the images acquired for a 70,800-ha rangeland watershed in Wyoming.

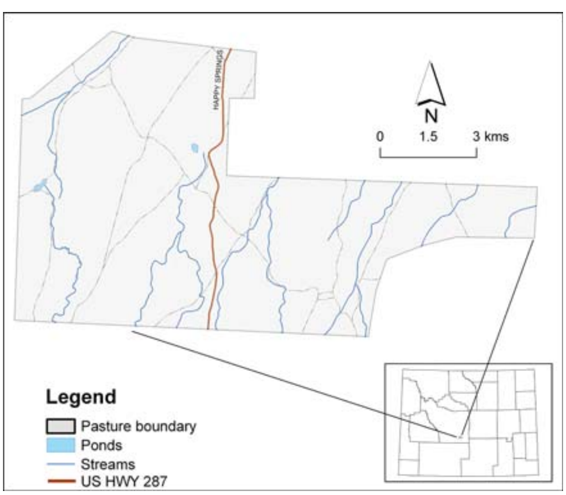

Fig. 1 Location of the study area in Wyoming, USA

SamplePoint analysis

SamplePoint is a digital 'pointframe' designed for point sampling digital images. With 1 mm GSD ground-acquired images it is has comparable accuracy to conventional field-methods for ground-cover measurements (Booth et al. 2006b). The program loads the images from a specified data base then systematically locates a user-defined number of sample points in the image—in this study we used 100 and each image had about a 3 × 4 m field-of-view. The software takes the user from one sample point to the next so that errors from double counting or missing a point are avoided. SamplePoint identifies each sample point by 4 red, 1-pixel-thick lines in a crosshair pattern that surround but do not cover, the sample-point pixel. Thirty buttons under the image are labeled for users to identify designated ground-cover characteristics. When a user classifies a point by clicking a button, the user's classification is saved to the database and the next point automatically shows up in the image window at the user-defined zoom level. Labels can be user-defined and we defined 16 categories: bare ground, litter, rock, biological crust, perennial grass, annual grass, perennial forb, annual forb, little sagebrush (*Artemisia arbuscula* Nutt. ssp. *arbuscula*), silver sagebrush (*Artemisia cana* Pursh), big sagebrush (*Artemisia tridentata* Nutt. ssp. *wyomingensis* Beetle and Young), Greene's rabbitbrush (*Chrysothamnus greenei* (Gray) Greene), greasewood (*Sarcobatus vermiculatus* (Hook.) Torr.), spineless horsebrush (*Tetradymia canescens* DC.), plains pricklypear (*Opuntia polyacantha* Haw.), and unknown. The software allows a user to zoom in or out as needed to understand the context or detail of an image pixel.

Measuring vegetation cover (%) using VegMeasure

We used VegMeasure v1.6.0, a software program developed at Oregon State University to measure plant cover on rangeland (Louhaichi et al. 2001; Johnson et al. 2003). VegMeasure quantifies areas of specific color, and does so for large batches of digital images through rapid binary classification. The green leaf algorithm (Louhaichi et al. 2001) was used to measure green cover and the blue band and brightness algorithms (Johnson et al. 2003) were used to measure bare ground. The blue band and brightness algorithms were used for bare ground because, in our experience, they more accurately separated bare ground from other parameters of ground cover. The detection threshold in VegMeasure is a pre-process user-adjustable method in which users are presented with side by side views of the original image and its simplified, black and white binary-classified depiction. The threshold for the characteristic under consideration is manipulated looking at the original color image. To objectively calibrate the threshold we used SamplePoint software (Booth et al. 2006b) to classify a 10% subset of the images by setting the threshold to reflect the SamplePoint measure of vegetative cover (Booth et al. 2005b, 2006b). SamplePoint has a 98% potential accuracy and a 92% practical accuracy, the difference being due to the pixel mixing inherent in imaging methods (Booth et al. 2006b).

Physiographic data

Each VLSA image is geocoded by the Track'Air system using the system's GPS (Booth and Cox 2006). Image centerpoints were added as a layer to a GIS (ArcView 3.3, ESRI, Redlands, CA, USA) containing a digital elevation model (DEM) acquired from the Wyoming Geographic Information Science Center (WYGISC, University of Wyoming, Laramie, WY, USA). The DEM was used to generate aspect and slope raster layers. Using the StatMod extension (Garrard 2002), all VLSA image centerpoints were queried for elevation, aspect and slope.

Landsat TM5 data

A cloud-free, TM5 scene (Path 36 - Row 30) acquired by Landsat on June 2nd, 2004 was obtained from the Upper Midwest Aerospace Consortium (UMAC). The scene was corrected for geometric and terrain distortions at the US Geological Survey—Earth Resource Observation Satellite Data Center in Sioux Falls, SD (USA). Raw digital numbers associated with the TM5 pixels were converted to at-satellite radiance using gain and offset values provided by the USGS (Markham and Barker 1986; Chander and Markham 2003). Using ERDAS Imagine® software (Atlanta, GA, USA) geographic location of each VLSA image (center point) was located on the Landsat image. Mean reflectance values in each band were obtained for the 162 VLSA images. Several transformed bands and vegetation indices were derived from the six multi-spectral bands of Landsat image (Table 1). Image transformation methods were used to reduce the dimensionality of the six Landsat bands to fewer bands or indices that could be related

Table 1 Transformed bands and indices derived from Landsat data that were used in this study

Name
Greenness Condition Index (GI): Band 4/Band 3
Normalized Difference Vegetation Index (NDVI): Band 4 − Band 3/Band 4 + Band 3
Vegetation Condition Index (VCI): Band 7/Band 4
Mid-IR/Red Reflectance Index (MIRI): Band 7 − Band 3/Band 7 + Band 3
Tasseled Cap Brightness: 0.29 Band 1 + 0.25 Band 2 + 0.48 Band 3 + 0.56 Band 4 + 0.44 Band 5 + 0.17 Band 7
Tasseled Cap Greenness: − 0.27 Band 1 − 0.22 Band 2 − 0.55 Band 3 + 0.72 Band 4 + 0.07 Band 5 − 0.16 Band 7
Tasseled Cap Wetness: 0.14 Band 1 + 0.18 Band 2 + 0.33 Band 3 + 0.34 Band 4 − 0.62 Band 5 − 0.42 Band 7

to certain vegetation phenomenon (Jenson 2000; Campbell 2002).

The 162 VLSA data points were randomly divided into two groups. Approximately two thirds (or 105) of the data points were used for assessing the relationship between the percent vegetation estimated from the photos and Landsat image. The remaining one third (or 57) of the data points were set aside for validation.

Regression model development and validation

Stepwise multivariate regression analysis was used to select a subset from the six multi-spectral Landsat bands that accounted for most of the variability in the dependent variable (Montgomery and Peck 1992; Sivanpillai et al. 2006). We used an alpha value of 0.05 as the criteria for retaining a variable that was selected in each step. The vegetation-cover measurements (dependent variable) derived from VLSA imagery using VegMeasure software were regressed against the following four sets of independent variables: (1) six Landsat bands, (2) six Landsat bands and physiographic data, (3) seven transformed bands described in Table 1, and (4) seven transformed bands and physiographic data. Independent variables of the final model were selected based on a combination of both their individual contribution to the model and the overall adjusted R^2 value. A similar procedure was repeated with vegetation-cover measurements derived from the SamplePoint software.

Regression models developed for predicting vegetation cover were validated using the 57 data points that were set aside. VegMeasure cover measurements and estimates derived from the four regression models were compared for assessing the adequacy of the regression models. This was followed by a comparison of the SamplePoint measurements and estimates derived from the four regression models. We also measured the correlation between SamplePoint and VegMeasure data. To determine if the SamplePoint and VegMeasure data sets were statistically independent of each other and that an assumption of homoscedasticity was valid even though the VegMeasure detection threshold was calibrated using SamplePoint, we tested the null hypothesis that the mean of regression residuals (the correlation coefficient is identical to the slope of the regression line) was not equal to zero.

Results

Model calibration

The regression model containing Landsat bands 1 (blue), 3 (red), 5 (near-infrared 2) and 7 (mid-infrared) was the best subset among the 6 raw Landsat bands to predict the percent vegetation measured by VegMeasure from 1 GSD (100-m AGL) VLSA imagery (Table 2). All the independent variables were significant in the regression model ($F = 29.16$; $P < 0.001$) and the adjusted R^2 value was 52%. The root mean square error associated with this model was 8. However, the regression model containing the Landsat bands 1, 3 and 7 and elevation was the best predictor of measured percent vegetation. All four independent variables in the above

Table 2 Models selected by the stepwise regression procedure when percent vegetation estimate, derived from VLSA imagery using VegMeasure software, were regressed against combinations of Landsat (original and transformed) bands and physiographic data as independent variables

Landsat TM5 bands
% cover = 2.3 + 0.68 Band 5 − 1.91 Band 7 − 2.12 Band 3 + 2.45 Band 1
Adjusted R^2 = 52%; RMSE = 8.2
Landsat TM5 bands and physiographic data
% cover = −308 + 0.16 Elevation − 0.98 Band 7 − 1.64 Band 3 + 2.27 Band 1
Adjusted R^2 = 65%; RMSE = 7.0
Transformed Landsat TM5 bands
% cover = 870 − 965 Band 7/Band 4 + 1159 MIRI − 1.9 TC_B − 12 TC_G − 3.7 TC_W
Adjusted R^2 = 55%; RMSE = 8.0
Transformed Landsat TM5 bands and physiographic data
% cover = 347 − 744 Band 7/Band 4 + 1043 MIRI − 1.4 TC_B − 10 TC_G − 2 TC_W + 0.15 Elevation
Adjusted R^2 = 67%; RMSE = 6.8

All regression models significant at 95% level ($\alpha = 0.05$)

regression model were significant ($F = 49.95$; $P < 0.001$) and the adjusted R^2 value increased to 65%. Reflectance values recorded by Landsat bands 3 and 7 decreased with increases in vegetation cover as measured by VegMeasure (inversely proportional), whereas values in band 1 increased with vegetation cover. Elevation was the only physiographic variable included in the model. The root mean square error associated with this model was 7.

Among the transformed Landsat bands, the regression model containing Vegetation Condition Index (Band 7/Band 4), mid-IR/Red reflectance index (MIRI), and tasseled cap brightness, greenness and wetness bands was the best subset ($F = 26$; $P < 0.001$) to predict the measured percent vegetation (Table 2). The adjusted R^2 value was 55% and this was only 3% more than the model containing raw Landsat bands. VCI, MIRI, tasseled cap brightness, greenness and wetness bands, and elevation (m) were the best subset ($F = 36$; $P < 0.001$) to predict the percent vegetation (Table 2). This model had the highest adjusted R^2 value of 67% ($n = 105$) and all six transformed bands were significant ($F = 36.7$; $P < 0.001$). MIRI values were directly proportional to percent vegetation content whereas all other independent variables included in this model were inversely proportional to percent vegetation cover. Elevation was the only physiographic variable included in the model. The root mean square error associated with this model was 6.8.

The regression model containing Landsat bands 5 (mid-infrared1) and 7 (mid-infrared2) was the best subset ($F = 12.87$; $P < 0.001$) among the 6 raw Landsat bands to predict the percent vegetation measured by SamplePoint, and the adjusted R^2 value was 19% (Table 3). Inclusion of elevation did not improve the overall significance ($F = 9.8$; $P < 0.001$), nor adjusted R^2 value (19%). Reflectance

Table 3 Models selected by the stepwise regression procedure when percent vegetation estimate, derived from VLSA imagery using SamplePoint software, were regressed against combinations of Landsat (original and transformed) bands and physiographic data as independent variables

Landsat TM5 bands
% cover = 86.7 − 1.38 Band 7 + 0.56 Band 5
Adjusted R^2 = 19%; RMSE = 9.0
Landsat TM5 bands and physiographic data
% cover = 5.6 − 1.11 Band 7 + 0.4 Band 5 + 0.04 Elevation
Adjusted R^2 = 19%; RMSE = 9.0
Transformed Landsat TM5 bands
% cover = −95.4 + 1150 NDVI − 89.9 MIRI − 0.45 TC_B − 6.4 TC_G
Adjusted R^2 = 20%; RMSE = 8.9
Transformed Landsat TM5 bands and physiographic data
% cover = −95.4 + 1150 NDVI − 89.9 MIRI − 0.45 TC_B − 6.4 TC_G
Adjusted R^2 = 20%; RMSE = 8.9

All regression models significant at 95% level ($\alpha = 0.05$)

values recorded by Landsat band 7 decreased with increases in vegetation cover as measured by SamplePoint (inversely proportional), whereas band 5 values increased with vegetation cover. The root mean square error was 9 in both models.

Among the transformed Landsat bands, the regression model containing Normalized Vegetation Difference Index (NDVI), MIRI, and tasseled cap brightness and greenness bands was the best subset ($F = 7.5$; $P < 0.001$) to predict the measured percent vegetation (Table 3). Inclusion of elevation values did not improve the overall significance ($F = 7.5$; $P < 0.001$) or the adjusted R^2 value (20%). The root mean square error associated with this model was 8.9.

Model validation

Two models that included the elevation as an independent variable were selected and validated using the 57 observations that were set aside earlier (Table 2). Predicted values from the regression models were compared with the percent vegetation derived from VLSA imagery using VegMeasure (Fig. 2a, b) and checked for model adequacy. Vegetation cover, as measured by VegMeasure from VLSA imagery, was significantly correlated to the predicted values using both raw ($r = 0.83$, $P < 0.001$) and transformed ($r = 0.86$, $P < 0.001$) Landsat bands. Points were spread above and below the 1:1 line in the 20% to 50% vegetation cover range. In the lower ranges (<20%) both models tend to over-predict the percent vegetation cover and in the higher ranges (>55%) the models under-predict the values. Since the models developed using SamplePoint measurements had lower R^2 values (Table 3), the validation process did not yield any insights regarding the relationship between the measurements and Landsat reflectance values.

Correlation between VegMeasure and SamplePoint measurements

The percent cover values obtained from VegMeasure and SamplePoint were well correlated ($r = 0.64$, $P < 0.001$) and the assumption of data-set homoscedasticity was justified (residual mean = 0.001, $P = 0.99$); however, for most of the points the VegMeasure estimates were lower than the SamplePoint estimates (Fig. 3). All types of vegetation including their non-chlorophyll parts (stems) were included in SamplePoint whereas VegMeasure used reflectance values. This could explain the lower values obtained from the VegMeasure protocol.

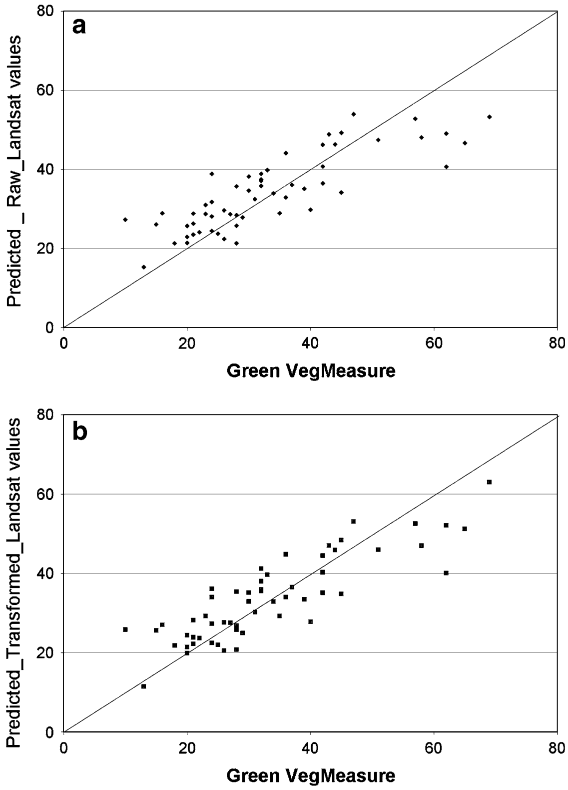

Fig. 2 Regression of vegetation cover derived from VLSA imagery with models involving raw (**a**) and transformed (**b**) Landsat bands (Table 1)

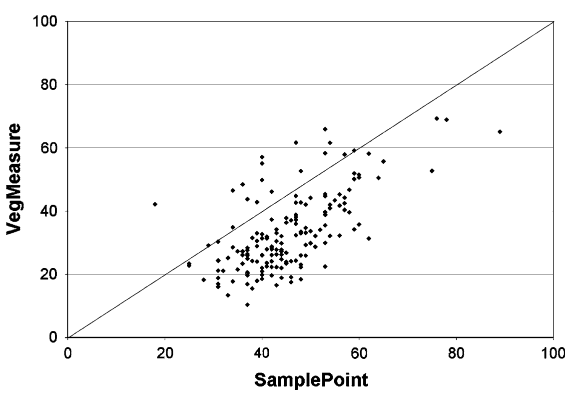

Fig. 3 Scatter plot of the percent vegetation cover estimates obtained from the aerial photos through the SamplePoint and VegMeasure sampling protocols ($r = 0.64$)

Discussion

VegMeasure and Landsat

The regression model with a subset of transformed Landsat bands and elevation values was able to account for 67% of the variance in the percent vegetation derived from VegMeasure, whereas a similar model with raw Landsat bands accounted for 65% (Table 2). Models with Landsat bands were able to account for only 52% and 55% of the variability in the vegetation estimates derived from VegMeasure. Several factors on the ground could have contributed to the differences observed between Landsat reflectance values and VegMeasure values. First, the reflectance of wet soil in the mid infrared region is lower in comparison to the reflectance values of dry soil of the same type. Second, numerous studies have demonstrated the near infrared (band 4) is a better predictor of vegetation biomass than are bands 1 (blue) and 3 (red). However, the reflectance values of band 4 are also influenced by soil moisture. The presence of wet soil patches following snow melt could have resulted in differences in the near infrared reflectance values. In addition, background soil color could have also contributed to the differences though the vegetation cover could have been similar. Todd et al. (1998) found the red band (band 3) to be a useful discriminator of vegetation in semi-arid regions, since the reflectance values are a combination of bright soil background and some dry vegetation. The regression model using the transformed Landsat bands increase the adjusted R^2 by only 3%. Inclusion of tasseled cap wetness band in both models (Table 2) indicates that soil moisture could have influenced the reflectance values.

Incorporating elevation values improved the predictive power of the regression model. Increasing elevation in this pasture was correlated with increasing bare ground (Booth et al. unpublished data) and thus with greater soil reflectance. The observed increase in bare ground at the higher elevations of the pasture could be due to a decrease in plant cover—particularly rhizomatous grasses—resulting from lower water infiltration and storage. The soils in this area often appear to be of coarser materials than soils at lower elevations. The higher-elevations *within this pasture* do not appear to receive the precipitation nor have the abundance of rock that might account for less bare ground at elevations on Green Mountain above the Hay Press Creek Pasture.

That elevation was a significant variable in the regression models (raw and transformed Landsat bands) is indicative of the ability of TM data to capture important ecological differences that can be correlated with finer data. Exclusion of slope and aspect as a significant independent variable indicates either these variables were not influencing the vegetation reflectance values or Landsat instruments were not sensitive enough to capture the differences.

SamplePoint, Landsat, and VegMeasure

Regression models using SamplePoint measurements as the dependent variable with combinations of Landsat data accounted for only 20% of the variance (Table 3). Mid infrared bands (5 and 7) accounted for the variability in SamplePoint measurements. Elevation was not a major contributor to the models using SamplePoint measurement and the absence of a significant relationship with the blue and red bands (1 and 3) indicates a lack of influence from the higher-elevation bare ground—thus highlighting the difference between SamplePoint and VegMeasurement. The degree of association between SamplePoint measurements and Landsat reflectance values were lower, though significant. Landsat and VegMeasurement values were based on reflectance, whereas SamplePoint measurements included spectral, texture, and context information derived through human interpretation. SamplePoint measurements were analogous to an inventory of various plant life forms irrespective of their reflectance characteristics. For example, when a SamplePoint user found pixels that fell on non-green parts of vegetation (live stems), it was included in the vegetation class.

The difference between protocols and high and low values might also be due to the fact that VLSA data contain some motion blur at the pixel level. Blur increases the amount of judgment a SamplePoint user must exercise and therefore increases the susceptibility of users to a bias for green color (Booth et al. 2005a, b). It is possible that in addition to assigning brown stem vegetation to total plant cover, there were also a percentage of drab categories (bare ground, rock, litter) that were classified as green due to the combination of motion blur and human bias. The differences in the methods suggests that accurate

Landsat analysis may be enhanced by developing correlations among SamplePoint and VegMeasure analyses, and between VegMeasure and Landsat data. Understanding how these separate analyses relate to each other may open a door that will allow Landsat data to be used to signal subtle, but ecologically important change and a need for a VLSA-type survey to identify and quantify the change.

Application to rangeland monitoring

A careful assessment of bare-ground measurement accuracy implies that at 1-mm GSD, SamplePoint and VegMeasure are 90% and 80% respectively; but, the latter is true only where there is a clear spectral separation between ground-cover characteristics (Booth et al. 2006b). VegMeasure will batch process 5-megapixel images at about 1 image/s (Booth et al. 2005b) and 11 megapixel images at <10 sec/image. It requires about 15 min for a person to read 100 points on an image using SamplePoint. Therefore, we recommend the use of VLSA and VegMeasure with Landsat for modeling extensive land areas with good contrast between ground-cover characteristics where ~80% is an acceptable level of accuracy. Where greater accuracy is required or where the spectral separation of ground-cover characteristics is not good, we recommend the use of VLSA and Sample-Point with Landsat but emphasize that more work is required to develop a better relationship between SamplePoint cover data and Landsat bands or indexes.

Conclusions

Regression models incorporating elevation values and Landsat bands as independent variables were better predictors of range vegetation cover ($R^2 = 65$–67%; $P < 0.001$) than those models containing only Landsat bands ($R^2 = 52$–55%; $P < 0.001$). However the ability of Landsat bands to predict vegetation cover at the low (<20%) and high (>55%) ranges is somewhat diminished. Landsat reflectance values accounted for more of the variability in the percent vegetation cover measurements derived from Veg-Measure protocol ($R^2 = 52$–67%; $P < 0.001$) than from those derived from the SamplePoint protocol ($R^2 = 19$–20%; $P < 0.001$). VLSA imagery can be used to calibrate Landsat data for estimating percent vegetation in semi-arid rangelands, thereby reducing the need to conduct expensive field and plot surveys. Calibrated Landsat data can be used to model rangeland vegetation conditions in Wyoming and similar semi-arid environments but more work is needed to improve the models relating VLSA and Landsat data.

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References

Beetle AA (1960) A study of sagebrush. The section *Tridentatae* of *Artemisia*. University of Wyoming, Agricultural Experiment Station Bulletin #368, Laramie, Wyoming

Booth DT, Cox SE (2006) Very large scale aerial photography for rangeland monitoring. Geocarto Int 21:27–34

Booth DT, Cox SE, Berryman RD (2006a) Precision measurements from very large-scale aerial imagery. Environ Monit Assess 112:293–307

Booth DT, Cox SE, Berryman RD (2006b) Point Sampling Digital Imagery with 'SamplePoint'. Environ Monit Assess 112:293–711

Booth DT, Cox SE, Meikle TW, Fitzgerald C (2005a) The accuracy of ground cover measurements. Rangeland Ecol Manage 59:179–188

Booth DT, Cox SE, Johnson DE (2005b). Detection-threshold calibration and other factors influencing digital measurements of bare ground. Rangeland Ecol Manage 58: 598–604

Campbell JB (2002) Introduction to remote sensing. The Guilford Press, New York

Chander G, Markham B (2003) Revised Landsat-5 TM radiometric calibration procedures and postcalibration dynamic ranges. IEEE Trans Geosci Remote Sens 41:2674–2677

Cingolani AM, Renison D, Zak MR, Cabido MR (2004) Mapping vegetation in a heterogeneous mountain rangeland using landsat data: an alternative method to define and classify land-cover units. Remote Sens Environ 92:84–97

FWS (Fish and Wildlife Service) (2005) Status review completed: greater sage-grouse not warranted for listing as endangered or threatened. http://news.fws.gov/NewsReleases/R9/4D0B98E6-DE22-18A8-5FBC25A1E928B298.html. Cited 3 Feb 2008

Garrard C (2002) StatMod. http://bioweb.usu.edu/gistools/statmod. Cited 3 Feb 2008

Gilmanov TG, Johnson DA, Saliendra NZ, Svejcar TJ, Angell RF, Clawson KL (2004) Winter CO2 fluxes above sagebrush-steppe ecosystems in Idaho and Oregon. Agric For Meteorol 126:73–88

Homer CG, Ramsey RD, Edwards TC, Falconer A (1997) Landscape cover-type modeling using a multi-scene TM mosaic. Photogramm Eng Remote Sens 63:59-67

Hostert P, Röder A, Hill J (2003) Coupling spectral unmixing and trend analysis for monitoring of long-term vegetation dynamics in Mediterranean rangelands. Remote Sens Environ 87:183–197

Ikeda H, Okamoto K, Fukuhara M (1999) Estimation of aboveground grassland phytomass with a growth model using Landsat TM and climate data. Int J Remote Sens 20:2383–2294

Jensen JR (2000) Introductory digital image processing: a remote sensing perspective. Prentice Hall, New Jersey

Johnson DE, Vulfson M, Louhaichi M, Harris NR (2003) VegMeasure v.1.6 user's manual. Department of Rangeland Resources, Oregon State University, Corvallis, Oregon

Kolb KJ, Sperry JS (1999) Differences in drought adaptation between subspecies of sagebrush (Artemisia Tridentata). Ecology 80:2373–2384

Kozar B, Lawrence R, Long D (2002) Soil phosphorous and potassium mapping using a spatial correlation model incorporating terrain slope gradient. Precis Agric 3: 407–417

Louhaichi M, Borman MM, Johnson DE (2001) Spatially located platform and aerial photography for documentation of grazing impacts on wheat. Geocarta Int 16:63–68

Markham BL, Barker JL (1986) Landsat MMS and TM post-calibration dynamic ranges, exoatmospheric reflectances and at-satellite temperatures, Landsat Technical Note 1. Earth Observation Satellite Co., Lanham, MD

Montgomery DC, Peck EA (1992) Introduction to linear regression analysis, 2nd edn. John Wiley & Sons, New York

Morgan JA, Mosier AR, Milchunas DG, LeCain DR, Nelson JA, Parton WJ (2004) CO2 Enhances productivity, alters species composition, and reduces digestibility of short-grass steppe vegetation. Ecol Appl 14:208–219

NS-GCT (Nevada Sage-Grouse Conservation Team) (2004) Sage-grouse conservation plan for Nevada and eastern California. Nevada Department of Wildlife, Reno, Nevada, 108 pp. Available at http://www.ndow.org/wild/conservation/sg/plan/SGPlan063004.pdf cited 3 Feb 2008

Schino G, Borfecchia F, Cecco LD, Dibari C, Iannetta M, Martini S, Pedrotti F (2003) Satellite estimate of grass biomass in a mountainous range in central Italy. Agrofor Syst 59:157–162

Seefeldt SS, Booth DT (2006) Measuring plant cover in sagebrush steppe rangelands: a comparison of methods. J Environ Manage 37:703–711

Sivanpillai R, Smith CT, Srinivasan R, Messina MG, Wu XB (2006) Estimation of managed loblolly pine stand age and density with Landsat ETM + data. For Ecol Manage 223:247–254

Todd SW, Hoffer RM, Milchunas DG (1998) Biomass estimation on grazed and ungrazed rangelands using spectral indices. Int J Remote Sens 19:427–438

West NE (1999) Accounting for rangeland resources over entire landscapes. In: Eldridge D, Freudenberger D (eds) People and rangelands: building the future. Proceedings of the VI International Rangeland Congress, Queensland 4814, Australia

Zambon M, Lawrence RL, Bunn A, Powell S (2006) Effect of alternative splitting rules on image processing using classification tree analysis. Photogramm Eng Remote Sens 72:25–30