Ecological Indicators 43 (2014) 297–305

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Assessment of sagebrush cover using remote sensing at multiple spatial and temporal scales

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ARTICLE INFO

Article history:
Received 19 September 2013
Received in revised form 8 March 2014
Accepted 17 March 2014

Keywords:
Rangeland assessment
Landscape management
Remote assessment
Monitoring
Remote sensing

ABSTRACT

Rangelands occupy a large portion of the Earth's land surface and provide many ecosystem services to human populations around the world. Increasingly, however, the ability of rangelands to continue providing these services is challenged by anthropogenic influence. There is an urgent need to monitor changes in rangelands through time and across large geographic areas. Current field-based methods used to assess and monitor rangelands are limited because of their inability to account for spatial and temporal variation. An alternative approach is presented to assess rangelands using high resolution imagery as enhanced ground samples and multi-spatial remote sensing imagery to quickly, cheaply, and effectively map basic land cover components. High-resolution, ground-based natural color vertical photography captures, in space and time, percent cover of vegetative and abiotic components at the plot level. This imagery maintains a visual history of percent cover allowing other investigators the ability to repeat the observation or use other sampling techniques to extract improved or additional information. These plot-based measures are then linked to airborne or satellite acquired imagery allowing for extrapolation of ground measurements across large landscapes. Linking plot-based measures to remotely sensed imagery can allow for documentation of change across the past 30 years utilizing Landsat imagery. Our process was applied to a sagebrush-steppe landscape in northern Utah with promising results. Extrapolation of percent vegetation cover data extracted from ground-based natural color vertical photography to 1 m resolution Ikonos imagery using regression tree analysis resulted in an overall R^2 value of 0.81 while an extrapolation to 30 m Landsat Thematic Mapper resulted in an R^2 of 0.90 using a 5-fold cross-validation. A comparison between independently acquired ground measurements from multiple time intervals showed a moderately strong correlation of $R^2 = 0.65$ for Landsat Thematic Mapper. This technique has great potential to place land cover change and rangeland health in a contextual perspective that has not been available before. In this way, past management practices can be evaluated for their effectiveness in altering basic cover components of rangelands. With this hindsight, improved management prescriptions can be developed providing a valuable tool in assessing public land grazing allotments for renewal or habitat quality for sensitive wildlife species like greater sage-grouse.

1. Introduction

Rangelands are widely distributed and occupy a large portion of the world's available land. Estimated global land area of rangelands varies widely from as little as 30% to nearly 70% based on the definition of rangelands (Lund, 2007; Breckenridge et al., 2008; Food and Agriculture Organization of the United Nations, 2009). Nonetheless, rangelands support almost one-third of the global human population, store about half of the global terrestrial carbon, support 50% of the world's livestock, and contain over one-third of the biodiversity hot spots (James et al., 2013). The monitoring and assessment of rangelands is thus of critical importance.

Monitoring of rangelands, however, is complicated by the high degree of spatial and temporal variation in vegetation and soil. To provide meaningful information about rangelands requires an evaluation across large landscapes and over extended periods of time (Booth and Tueller, 2003; Palmer and Fortescue, 2003; Washington-Allen et al., 2006). Moreover, semi-arid and arid rangelands are significantly influenced by the quantity and timing

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http://dx.doi.org/10.1016/j.ecolind.2014.03.014
1470-160X/

of precipitation creating extreme inter-annual variation (Noy-Mier, 1973; Sharp et al., 1990). Evaluating rangelands and their response to specific management (e.g., grazing) can therefore be difficult (Pickup et al., 1998; Blanco et al., 2009). Traditional field-based monitoring is usually insufficient to accurately assess ecological status or to detect important changes across large geographic areas outside of the plot extent (National Research Council, 1994; Donahue, 2000). Increasing the number of traditional ground-based monitoring plots across large spatial and temporal scales is often prohibitively expensive and still has limited evaluative capabilities (Friedel et al., 1993; Bastin et al., 1993; West, 1999).

The inadequacies of traditional ground-based sampling for rangeland assessment could be the reason that the largest rangeland management entity in the United States, the United State Department of Interior – Bureau of Land Management (USDI-BLM), has only inventoried an average of 0.6% of its national land holdings annually (~113 million ha) from 1998 to 2007, resulting in 5.4% being inventoried over this time period (USDI-BLM, 2012). Often, land-use plans are renewed without formal assessment of rangelands as required by the National Environmental Protection Act (NEPA). Most grazing allotment renewals in the past few decades have been completed via a "grazing rider" attached to the Department of Interior's Appropriation Bill. This renewal process keeps in place the terms and conditions of previous allotment management plans without assessing whether "Standards and Guidelines" of rangeland health are satisfied. This lack of feedback limits the ability of land managers to improve knowledge of the systems' ecology and to respond adaptively (Boyd and Svejcar, 2009).

The application of remote sensing technology to rangeland assessment has the potential to remove some of these limitations. While coarse resolution remote sensing technology cannot, directly identify plant species, it has had success in determining percent ground cover using vegetation indices like the normalized difference vegetation index (NDVI) at coarse resolution like 30 m Landsat imagery. Percent ground cover is not, in itself, an indicator of range condition, but when assessed over large landscapes and over long time periods, the patterns of percent ground cover change caused by management action can be separated from changes due to climatic variability, soils, or geomorphology (Pickup et al., 1994, 1998).

Using remote sensing technology, Homer et al. (2012) mapped percent cover of basic vegetative components over big sagebrush (*Artemisia* sp.) landscapes of the western United States. They used regression tree analysis on multi-scale imagery with three nested spatial scales including traditional on-the-ground field sampling, Quickbird 2.4 m imagery, and Landsat 30 m imagery to predict percent cover. Additionally, NDVIs were created from Quickbird and Landsat imagery to predict cover. To assess the accuracy of the multi-scale and NDVI predictions, correlation coefficients were determined using a linear regression of the predicted values against independent ground-based vegetation measurements. The correlation coefficients of the nested multi-scale predictions were $R^2 = 0.51$ for Quickbird imagery and $R^2 = 0.26$ for Landsat imagery. The Quickbird and Landsat NDVI predictions were $R^2 = 0.18$ and $R^2 = 0.09$, respectively. These results, while promising for very large scale assessment and planning, are not precise enough on a scale to support local adaptive resource management.

The need for cost effective assessments of rangeland with high spatial resolution and improved accuracy for management applications has stimulated research in the use of high-resolution photography for rangeland assessment. High resolution, nadir photography can serve as a realistic ground plot. It is information rich, understandable to a broad base of people, and the unanalyzed information can be archived for future use. This ability to revisit imagery that documents actual field conditions at the time of collection is not possible through conventional field data collection

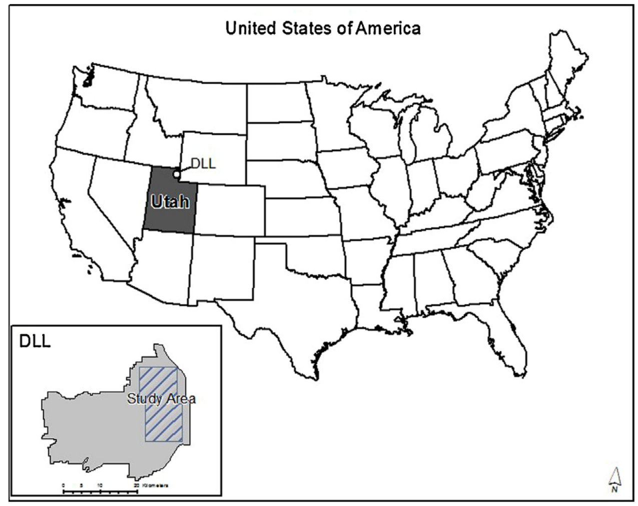

Fig. 1. Study area location in relation to the United States, Utah, and Deseret Land and Livestock (DLL). The actual study area is bounded north to south by 41.439° N and 41.258° N and east to west by 111.057° W and 111.195° W.

techniques. Archived field plot imagery can therefore be reviewed by many observers at later times using potentially improved or multiple techniques to record land cover. High resolution imagery, less than 1 cm, is being used by a number of researchers (e.g., Breckenridge et al., 2011; Cagney et al., 2011; Karl et al., 2012; Mirik and Ansley, 2012). Results to date are mixed, but strong correlation coefficients of $R^2 = \sim 0.90$ have been observed for bare ground. Using high resolution imagery, Pilliod and Arkle (2013) found that photography-based grid point intercept (GPI) in Great Basin plant communities was strongly correlated to line point intercept (LPI) but it was 20–25 times more efficient, identified 23% more plant species, and was more precise in determining percent cover. Furthermore, they found that GPI could precisely estimate cover of basic vegetation components when they exceeded 5–13% while LPI cover estimates had to exceed 10–30% cover for equal precision. Detecting change when percent cover is low is very important in arid lands where land cover is typically sparse.

The method presented in this paper integrates the use of high resolution photography as enhanced ground samples and as a training dataset for multiple scales of remotely sensed imagery. It models the percent cover of bare ground, shrub, and herbaceous vegetation cover across big sagebrush (*Artemisia* sp.) landscapes in the western United States. It can provide information on sagebrush dominated rangelands at spatial scales from millimeters to kilometers, across multiple years. We show that this method maps commonly used and functionally important cover types with considerable success and increased precision.

2. Methods

2.1. Study area

The study area is part of the 20,263 ha Deseret Land and Livestock (DLL) ranch in Rich County, UT, USA (Fig. 1) in the Middle Rocky Mountains physiographic region. The ranch ranges in elevation from 1928 to 2270 m. Annual precipitation has ranged from 11 cm to 40 cm with an average of 24 cm since 1897. Temperatures during this same period averaged a low of −18 °C in January and a high of 28 °C in July (Western Regional Climate Center, 1986). Dominant landcover types include short sagebrush (*A. nova* and *A. arbuscula*) and big sagebrush (*A. tridentata*). Where big sagebrush communities had been treated (mechanical, fire, or herbicide), crested wheatgrass (*Agropyron desertorum*) was dominant. The

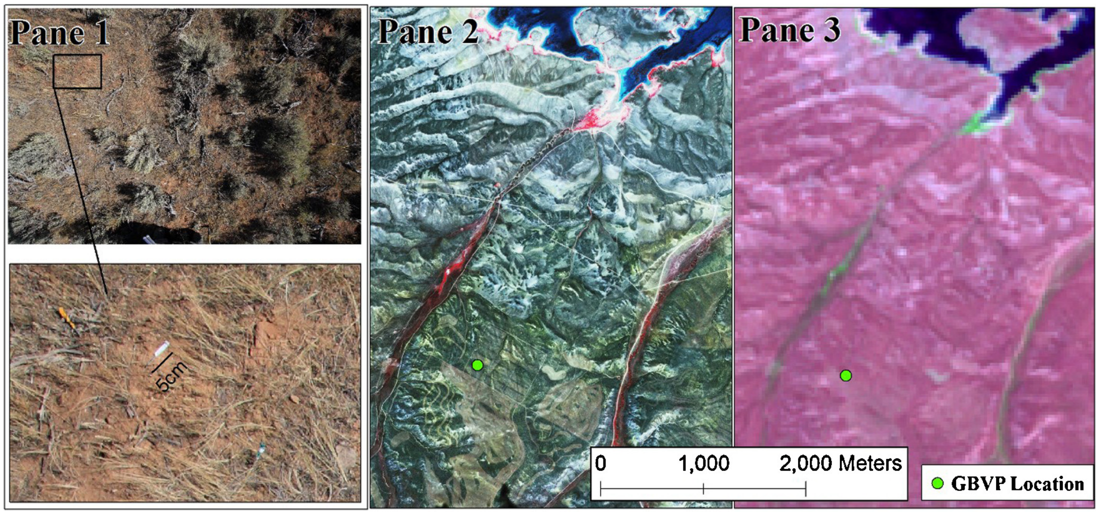

Fig. 2. Differences in detail of imagery used in the assessment of rangelands across multiple spatial and temporal scales. Pane 1 shows the high detail of the 2 mm GBVP imagery as well as the color coded nails used for accuracy assessment. Pane 2 displays the 1 m Ikonos imagery. Pane 3 illustrates the coarser 30 m Landsat imagery. Water and sparse vegetation are also discernable in Panes 2 and 3.

study area consisted of 12 ecological sites, four of which (semi-desert stony loam, semi-desert clay, upland loam, and semi-desert loam) accounted for 95% of the land area. Ecological sites are a distinctive kind of land with specific characteristics that differ from other kinds of land in its ability to produce a distinctive kind and amount of vegetation. Ecological sites and their descriptions are mapped and organized through the United States Department of Agriculture, Natural Resource Conservation Service (USDA-NRCS, 2012).

2.2. *Image processing and modeling*

To assess rangelands at different spatial and temporal scales, we focused on the basic ground cover types of bare ground, shrub, and herbaceous vegetation for several reasons. First, these basic cover types show less inter-annual variation associated with climatic conditions compared to responses of individual species. Second, they can be compared to ecological site descriptions which are benchmarks currently used in monitoring rangelands. Third, percent bare ground is indicative of water sequestration in a watershed because it is highly correlated to infiltration (Bailey and Copeland, 1961; Branson and Owen, 1970; Lusby, 1970; Peterson et al., 2009; Weber et al., 2009). Fourth, each of these general cover types can be discerned remotely at low cost across large spatial extents. Finally, the values of these basic ground cover types, when assessed remotely, can be helpful when making decisions that affect management decisions such as allotment renewals.

Using ground-based color vertical photography (GBVP) at 2 mm spatial resolution, we estimated canopy cover for each field site and used these estimates as training to model percent cover of each basic ground cover category across the study area using coarser satellite based (Ikonos 1 m and Landsat 30 m) imagery (Fig. 2). To model temporal changes in percent cover we used radiometrically normalized Landsat imagery collected across time to model the same general land cover types for each historic image.

2.2.1. *GBVP (2 mm resolution) Classification*

GBVP images consisted of digital photographs oriented vertically (nadir view) taken with an 18-megapixel, 10 mm focal length, Canon Digital Rebel T2i camera mounted to a boom attached to an All-Terrain Vehicle. Site locations were recorded with a high precision Trimble Omnistar Pro XS GPS with a real-time accuracy of 10 cm. All GBVP images were collected with the top of the image-oriented north to facilitate registration with other imagery. The image scale was calculated with the following equation where SAW = sensor array width, LH = lens height and FL = focal length:

$$\frac{\text{SAW} \times \text{LH}}{\text{FL}} = \text{Image Scale}$$

The image scale was multiplied by the length and the width of the image in pixels (Avery and Berlin, 1992) to create a precise (±10 cm) geographic footprint of the image (Fig. 3). Differences in terrain and ATV uphill or downhill orientation resulted in a difference in lens height and consequently image scale. On average, the

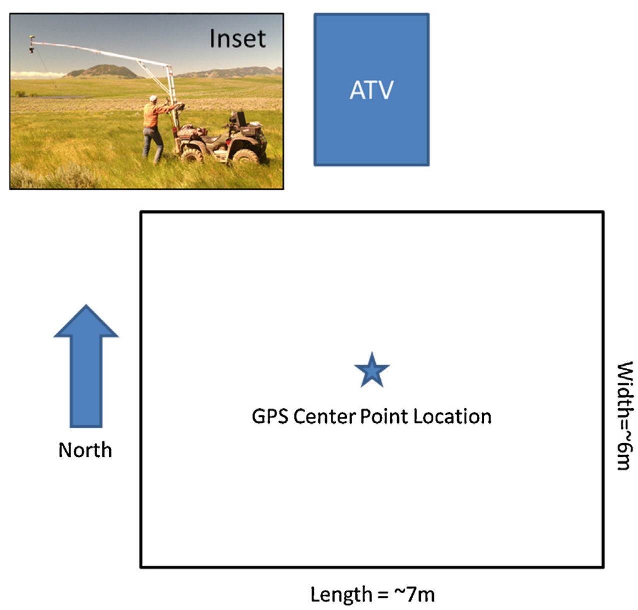

Fig. 3. This figure diagrams the logistics of the GBVP image footprint. The ATV is oriented north with the camera and GPS extended behind it. Because the center point of the photo is known along with the height and focal length of the camera lens, a very precise footprint of the image is delineate. The average cover of shrub, herbaceous, litter, and bare ground within the GBVP footprint serve as the enhanced on-the-ground sample which is the baseline training dataset for the multi-scale imagery. The Inset shows the actual GBVP platform.

lens height was 355 cm with a standard deviation of 24 cm, and the area of the footprint was 42 m^2 with a standard deviation of 5 m^2.

Eighty GBVP images were collected during late July and early August of 2010. This time frame corresponded to maximum vegetation greenness. Moreover, it minimized shadow as sun elevation is maximized during this time of year in the Northern Hemisphere. Images were also captured between 9:00 a.m. and 5:00 p.m. local time to minimize shadow effects. Sampling locations were restricted to areas of homogenous vegetation of at least 8.5 m by 5 m to match the nominal image footprint size. Sampling focused on capturing enough plots to provide a wide range of cover conditions. In other words, within the GBVP training dataset there are images that recorded low, medium, and high shrub, bare ground, and herbaceous cover.

After the GBVP images were collected, the percent cover was assessed for each of the 80 images by classifying the pixel color values into the three basic ground cover types as well as litter and shadow (Laliberte et al., 2010) using the Visual Learning Systems Feature Analyst Software 5.0.0.119™ (2010). For each image, a minimum of five samples for each of the ground cover types were digitized as polygons by visually assessing the image and digitizing small areas of the appropriate ground cover type. The average polygon size was 50 mm^2 with a standard deviation of 20 mm^2. These polygons served as training samples to classify the remaining image pixels on that image using the "Land Cover Feature" and "Manhattan Input Representation" algorithms within the Feature Analyst Software. This classification resulted in an estimate of percent cover for the basic cover types of shrub, herbaceous, litter, shadow, and bare ground for each GBVP footprint.

Each image was classified individually to overcome differences in soil color, degree of stone cover, and cryptobiotic cover between images. Because of the inability to differentiate between standing and laying litter all litter was classified as one class. Shadow was classified for each image but was not included as part of the percent cover of each category. We, therefore, assumed that shadow obscured ground cover in similar proportion across all four categories (shrub, herbaceous, litter, and bare ground). The influence of shadow can preclude the applicability of this technique to areas where a large portion of the canopy is composed of trees. However, the application of this method to low structured rangeland vegetation, like sagebrush, should result in relatively small errors from shadow if images are collected at high solar angles (Laliberte et al., 2010). Processing of GBVP images were performed by specialists with extensive field and image classification experience. Each GBVP image required approximately 1 h to process.

2.2.2. 1 m-resolution cover mapping

Ikonos imagery was acquired on August 11, 2010 and registered to 1 m National Agricultural Imagery Program (NAIP) imagery using a direct linear transform and 10 m digital elevation models with a root mean square less than 0.05 m. To map percent cover across the landscape, the results of the classification for each GBVP footprint were used to train the Ikonos 1 m, 4-band, imagery. Percent cover was modeled with regression tree analysis (RTA) (Homer et al., 2012) using the four Ikonos spectral bands (band 1, 445–516 nm; band 2, 506–595 nm; band 3, 632–698 nm; and band 4, 757–853 nm), as well as derived brightness and greenness (Horne, 2003), NDVI (band 4 − band 3)/(band 4 + band 3), green normalized difference vegetation index (GNDVI) (band 4 − band 2)/(band 4 + band 2) and a moisture normalized difference index (band 4 − band 1)/(band 4 + band 1) (Homer et al., 2012), as explanatory variables. A combination of a regression tree program in R (R Development Core Team, 2008), and ArcMap 10.1(ESRI, 2011) were used for analysis. R was used to create the predictive model and ArcMap was used to apply the model spatially for each image pixel. The output consisted of four canopy cover maps representing the percent cover of shrub, litter, herbaceous and bare ground.

2.2.3. Landsat thematic mapper (30 m) percent cover mapping

In order to model percent cover for the coarser spatial resolution Landsat imagery collected for the same summer (July 19, 2010) as well as through time, a similar regression tree model was developed for Landsat imagery using the Ikonos derived percent cover products as a source of training data. Once the model was developed and tested for the July 19, 2010 image, the same model was applied to Landsat imagery collected in multiple years from 1993 to 2006 and radiometrically normalized to the July 19, 2010 image. Level 1T Landsat images were downloaded from the United States Department of Interior-United States Geological Survey (USDI-USGS), Earth Explorer website (USDI-USGS, 2006) and re-projected to the UTM zone 12 NAD83 coordinate system to match other data layers in this study. The 2010 Landsat image was converted to percent reflectance (Chavez, 1996) and normalized for sun angle. To model three categories of canopy cover (shrub, herbaceous, and bare ground), the six reflective Landsat spectral bands (band 1, 450–520 nm; band 2, 520–600 nm; band 3, 630–690 nm; band 4, 760–900 nm; band 5, 155–175 nm; and band 7, 208–235 nm) were used. The same spectral indices that were extracted for the Ikonos image (brightness, greenness, NDVI, GNDVI, and moisture normalized index) as described above were also derived for the Landsat image using the appropriate Landsat bands.

The three Ikonos derived canopy cover maps of shrub, herbaceous, and bare ground were used as training data for the Landsat derived cover using RTA. We were unsuccessful in modeling litter cover with Landsat imagery and do not report it. In order to use the Ikonos continuous cover data as a training source, the Ikonos percent cover values were averaged (rounded to the nearest whole number) for each of the 136,083 Landsat pixels covering the study area. Hereafter, this will be referred to as Ikonos Averaged Continuous Cover (IACC). Because of computational limitations, a subset of 1000 IACC pixels was selected to create the RTA model.

The selection of the 1000 IACC pixel training subset proved crucial in the successful creation of RTA models for Landsat imagery. The non-linear relationship between multispectral reflectance and percent cover (Tucker, 1977; Curran, 1980) and the propensity of RTA to over-fit models (Lawrence and Wright, 2001) required a proper sampling of the variation in percent cover. An underrepresentation of pixels in the low percent cover categories (e.g., <10% shrub cover) is the outcome if samples are not carefully selected. To overcome this sampling problem a stratified sample based on a transformation that reapportioned the number of samples to include a higher proportion of low percent cover pixels was created. The results of this method proved to more closely match the Ikonos percent cover prediction than either a strict random or proportionate random sampling (Fig. 4). Therefore, 1000 IACC pixels were selected as a training sample by transforming the percent cover frequency of each of the three basic cover types using the following transformation:

$$\frac{1}{\text{percent cover value/number of occurrences}}$$

By applying this transformation, the resulting Landsat derived percent cover more closely matched the distribution of the Ikonos derived continuous cover.

The pixel frequency stratification specified how many IACC pixels to select from each one-percent cover increment (0%, 1%, 2%,. . .,30%, etc.). Samples selected for each percent cover category were selected based on those aggregated IACC pixels that had the lowest standard deviation values to ensure low landscape variation within the candidate Landsat pixels (Liu et al., 2004).

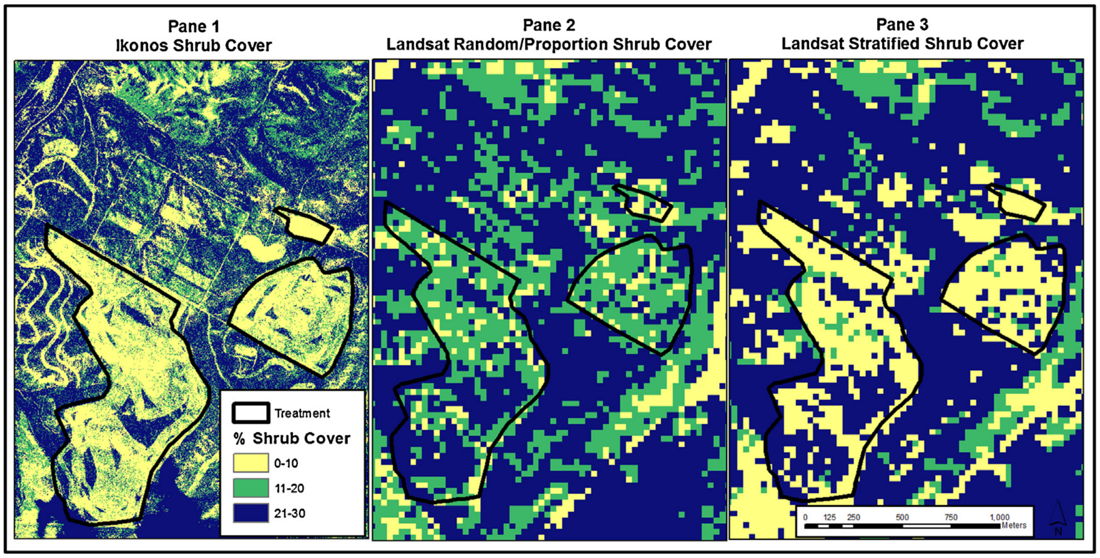

Fig. 4. This figure illustrates the need for selectively picking sample pixels instead of using a random or proportional sample. Pane 1 is the shrub percent cover estimated using the 1 m Ikonos imagery. Pane 2 illustrates the results of the shrub percent cover model of 30 m Landsat imagery if the samples are selected randomly or proportionally. Pane 3 demonstrates the results of the shrub percent cover model of 30 m Landsat imagery when sample selection is stratified and a higher percentage of low shrub cover pixels are used in the model.

Once a satisfactory model of percent cover of the three basic cover types was created for the 2010 Landsat image, it was applied to Landsat imagery collected in previous years to temporally assess percent cover. Historic July Landsat imagery was selected from the following years: 1993 and 1995–2006. There was no summertime cloud free image available for 1994. All images were downloaded and received the same pre-processing (conversion to reflectance and solar angle normalization) as the 2010 image. Additionally, multi-temporal images were radiometrically normalized to the 2010 image using a pseudo invariant features (PIF) process (Schott et al., 1988; Callahan, 2003; Sant, 2005; Booth et al., 2012).

2.3. Accuracy assessment methods

Accuracy of each output was assessed using several methods and datasets. Traditional on-the-ground cover sampling was used to assess the GBVP image classifications. With the 2010 percent cover models created from the Ikonos and Landsat imagery, a 5-fold cross validation was used to determine the accuracy and repeatability of the model. The percent cover of shrub derived from the Ikonos and Landsat imagery was further assessed using independently gathered on-the-ground techniques. Accuracy of temporal outputs was determined using historical sagebrush treatments. Changes in bare ground, shrub, and herbaceous cover were compared to expected changes in these components from other non-related studies.

2.4. GBVP accuracy method

The accuracy of the GBVP classification was determined using color-coded nails. This method was an adaptation of the on-the-ground cover sampling technique described by Daubenmire (1959). Three-hundred and sixty nails (5.08 cm in length) were wrapped in colored tape where each color was correlated to a basic cover type (white = bare ground, yellow = litter, green = herbaceous, and blue = shrub). The color-coded nails were then placed within 21 different GBVP footprints so that they would be visible in the image. The nails were placed in locations that were clearly one of the basic ground cover types. Each color-coded nail in the photo was identified and the location point buffered by 6 cm. If the majority of classified pixels within the buffer agreed with the color-coded nail, the cover type was correctly mapped.

2.4.1. Ikonos and Landsat accuracy methods

In order to estimate the repeatability of the model, a 5-fold cross validation process was used. The 5-fold cross validation estimated the expected level of fit of the percent cover models to the independent dataset that was used to train the model. This consisted of using different sample subsets within the training dataset to create five different models. In each of the five iterations, 80% of the total samples were randomly assigned as training and 20% as validation. The validation samples were regressed against the predicted values of the model to determine the correlation coefficient or R^2 value. The results are reported as a mean and standard deviation of the R^2 of the five iterations.

Additionally, accuracy was assessed using an independent study funded by the Wildlife Federal Aid Project W-82-R that investigated the effectiveness of six different sagebrush removal techniques against a control where sagebrush was not removed. This data set served as an independent validation of the remotely estimated shrub cover. The six sagebrush removal techniques as well as control plots were replicated three times. Each treatment plot consisted of a 1.1 ha strip (61 m by 183 m) surrounded by a 15 m buffer of untreated sagebrush. Blocks for each replication were separated by 40 m strips to allow adequate space for equipment to move from plot to plot (Fig. 5). Shrub cover was assessed in 2001 before treatments began. Following the treatments in 2002, shrub cover assessments were made for 2002, 2003, 2006, and 2010 (Summers, 2005). These assessments utilized a line-intercept technique (Herrick et al., 2005) to sample the 21 plots for shrub cover. The line-intercept shrub cover measurements from each of the 2010 shrub cover assessments were regressed against the average shrub cover of each of plots derived from the RTA to determine a correlation coefficient.

2.4.2. Temporal Landsat accuracy methods

The Landsat temporal percent cover predictions were assessed with two datasets. The first was the Wildlife Federal Aid Project W-82-R described above. The second validation data set consisted of large-scale historical sagebrush removal treatments. The Wildlife

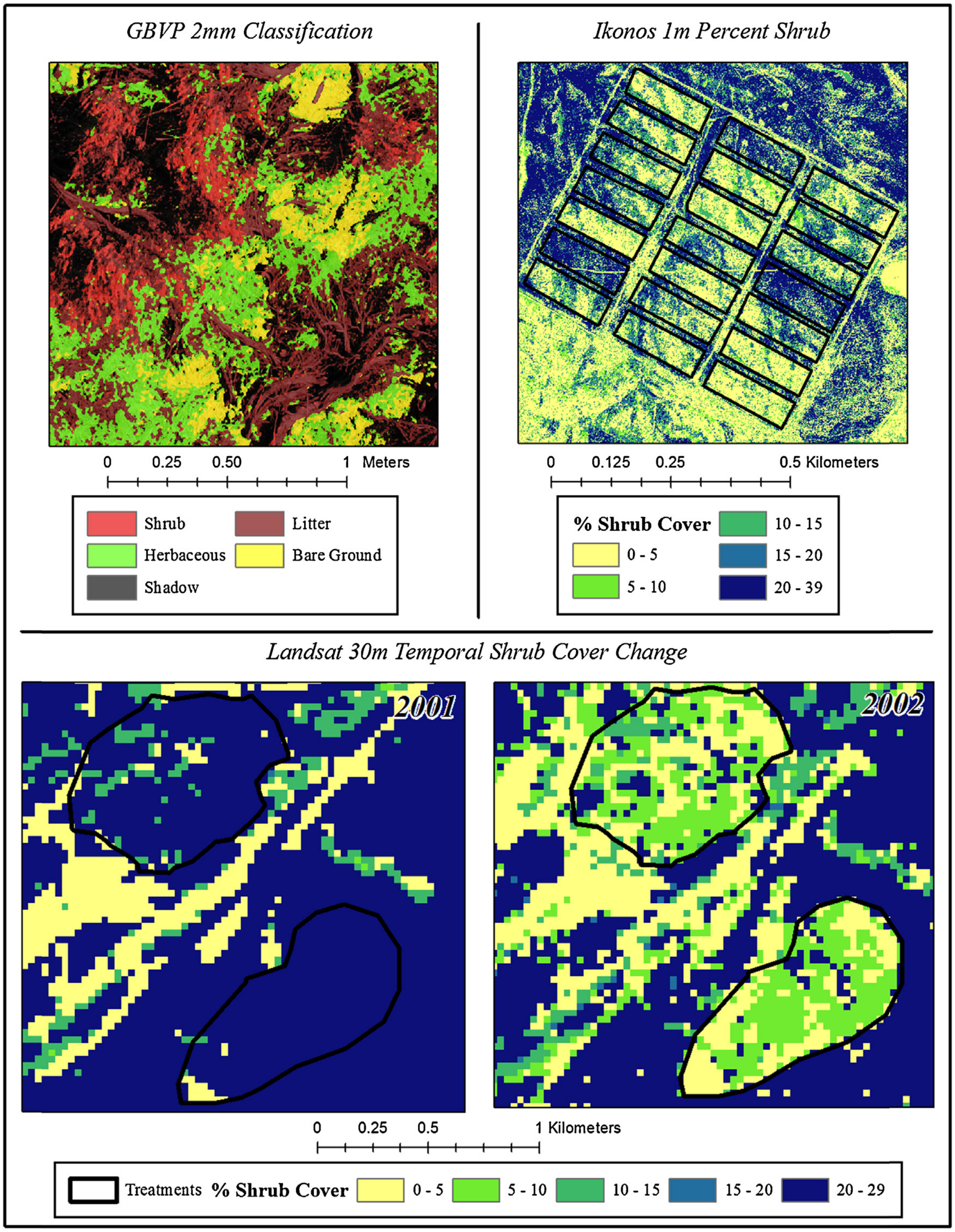

Fig. 5. Results of assessing percent cover on different image scales. The GVBP classification is illustrated in high detail in the upper left hand corner. The Wildlife Federal Aid Project W-82-R treatments are shown on the Ikonos shrub cover in the upper right hand corner. The Landsat temporal results (lower half) illustrate the difference in shrub cover before and after a treatment.

Federal Aid Project W-82-R validation set consisted of field-based shrub percent cover measurements in 2001 before sagebrush treatments and in 2002 after sagebrush treatments. The difference in each plot's percent shrub cover between 2001 and 2002 as measured with the line-intercept method was regressed against the average difference between the RTA derived percent shrub cover for 2001 and 2002 for each treatment polygon to determine the correlation coefficient. The second validation data set consisted of 11 large-scale sagebrush removal treatments from 1993 through 2006. These treatments included aerating, disking, and burning. The ability of the Landsat temporal predictions to detect change was also assessed using these treatments. For each treatment, a polygon was delineated within the treatment area and in an adjacent untreated area that occupied the same ecological site. The difference in the percent shrub cover of the treated polygon before and after the treatment was compared to the difference before and after the treatment within the untreated polygon. This measured change was compared to expected changes within sagebrush treatments

Table 1
The 5-fold cross validation of Ikonos and Landsat percent cover models. Both the Ikonos and Landsat imagery had high average R^2 values and when a 5-fold cross validation was performed on them with low standard deviations. This indicated the model was accurate and repeatable.

	Ikonos		Landsat	
Cover type	$\bar{x}\,R^2$	s	$\bar{x}\,R^2$	s
Bare ground	0.82	0.08	0.87	0.02
Herbaceous	0.81	0.13	0.90	0.01
Shrub	0.80	0.11	0.93	0.01

based on literature from other non-related sagebrush treatment studies.

3. Results

The color-coded nail assessment of the GBVP imagery resulted in an overall accuracy of 94%. Individual component accuracies were 99% for bare ground, 95% for litter, 92% for herbaceous, and 90% for shrub. For the Ikonos and Landsat imagery derived cover estimates, the 5-fold cross validation showed strong correlations between predicted values and the withheld training samples with very low standard deviations (Table 1) indicating that the model was accurate and repeatable. The predicted average shrub cover values from the 2010 Ikonos and Landsat RTA models were highly correlated to shrub cover collected independently on-the-ground on Wildlife Federal Aid Project W-82-R in 2010. The Ikonos RTA prediction had an R^2 value of 0.85 and p-value < 0.01. The Landsat RTA prediction had an R^2 value of 0.81 and a p-value < 0.01.

Shrub cover change predictions for 2001 and 2002 derived from Landsat imagery were assessed using the difference derived from the independent field-based Wildlife Federal Aid Project W-82-R data collected in 2001 and 2002. This resulted in a moderately strong correlation with an R^2 of 0.65 and a p-value < 0.01. Because treatments were small (60 m by 180 m) and not oriented directly north and south there was a considerable amount of pixel mixing when using the north-south oriented 30 m Landsat pixels. This geometric difference could have influenced the moderate correlation.

Within the 11 large-scale sagebrush removal treatments, Landsat derived estimates for treated plots showed an average shrub decrease of 15% versus untreated plots that had an average shrub increase of less than 1% (Fig. 6). On average, percent bare ground increased by 10% in the treated plots and did not change in the untreated plots. The change in average herbaceous cover was not significantly different between the treated and untreated plots. The results of the percent shrub cover measured with Landsat imagery were congruent with the findings of other sagebrush removal studies. Wambolt and Payne (1986) showed that multiple sagebrush removal techniques on average resulted in a 14% decrease of sagebrush. Fig. 5 illustrates the results of each of the different temporal and spatial scales analyzed.

4. Discussion

This study incorporated field-based high-resolution imagery, as an alternative to traditional field plots, to train satellite based remotely sensed imagery and extract relevant cover information continuously across a landscape. Estimates of percent cover derived from high spatial resolution Ikonos satellite imagery was then used to train Landsat imagery to estimate percent cover over a large landscape across multiple years. The combination of GBVP, Ikonos, and Landsat spatial and temporal scales provide a framework that gives a manager a current snapshot of percent ground cover that can be compared with historic imagery. The ability to estimate historic percent canopy cover provides important information to evaluate the effectiveness of previous management actions as well as guide future management decisions aimed at maximizing ecosystem services such as the production of food, fiber, domestic grazing, wildlife, recreation opportunities, carbon sequestration, and water quality and quantity.

The advantage of GBVP images is that investigators can record and preserve actual field conditions in space and time. This provides a more transparent and repeatable field-level estimation of canopy cover. Field-based high-resolution vertical imagery captures, in space and time, actual percent cover of the vegetation being measured. Because of this, a visual history of percent cover can be maintained for comparison with future assessments or applied to more advanced classification techniques. This repeatability of measurements makes field observations more transparent. Additionally, methodological tests have found that 2000 measurements per ground sample are necessary to estimate cover when that functional group's cover is less than 8% (Pilliod and Arkle, 2013). Each GBVP image contains 18 million measured data points.

Some of the practical limitations of using GBVP images include shadow in the images and the necessity of manually classifying each image. Using GBVP images where there is tall vegetative structure, late season, and or low sun angle will increase shadow and will likely result in poor results. The results reported in this manuscript come from vegetative structure less than 1 m. Manually classifying GBVP images takes an experienced technician an hour to adequately assess an image. The GBVP classifications in this manuscript where performed by the technician who also captured the image.

The Ikonos 1 m scale images were used to map percent canopy cover continuously across the landscape at high spatial detail – a capability outside the GBVP technique as well as traditional ground-based sampling. Mapping percent cover accurately across large landscapes provides land managers with evaluative power not available with limited point-based samples. The power of the Landsat 30 m derived percent cover maps provides not only the ability to extrapolate to larger landscapes, but also takes advantage of the unprecedented 39-year history of the Landsat program. This unique ability to capture rangeland percent cover for a significant time period provides managers with a contextual perspective that is not always (or ever was) available.

Enhanced ground sampling with high resolution, multiple spatial and temporal scale assessments can be used to address many pressing issues in range management. These include the landscape level estimation of percent cover, the temporal variation in percent cover, and assessing impacts due to disturbance and management prescriptions. These data can address the aforementioned problem of grazing allotment renewals. BLM grazing allotment renewal is dependent on the assessment of four standards of rangeland health. The first three standards are: (1) properly functioning watersheds; (2) properly functioning water, nutrient and energy cycles; and (3) water quality meeting state standards. Potentially, each of these standards can be addressed by estimating percent cover of bare ground within a watershed and how the extent bare ground has changed over time.

The fourth BLM standard is "habitat for a special status species". Currently, the greater sage-grouse (*Centrocercus urophasianus*) has been identified by the Endangered Species Act as a warranted species for protection. Sage-grouse are a species that depend on sagebrush communities throughout all phases of its life cycle. In the Sage-grouse Habitat Assessment Framework (HAF), Stiver et al. (2010) states that, "monitoring is a primary tool for applying effective adaptive management strategies in conservation and fulfilling the commitments in the Greater Sage-grouse Comprehensive Conservation Strategy". Johnson (1980) described four orders of habitat selection by sage-grouse across a range of scales. These orders are scale-dependent and give context to habitat conservation so policies and practices can work congruently. The process

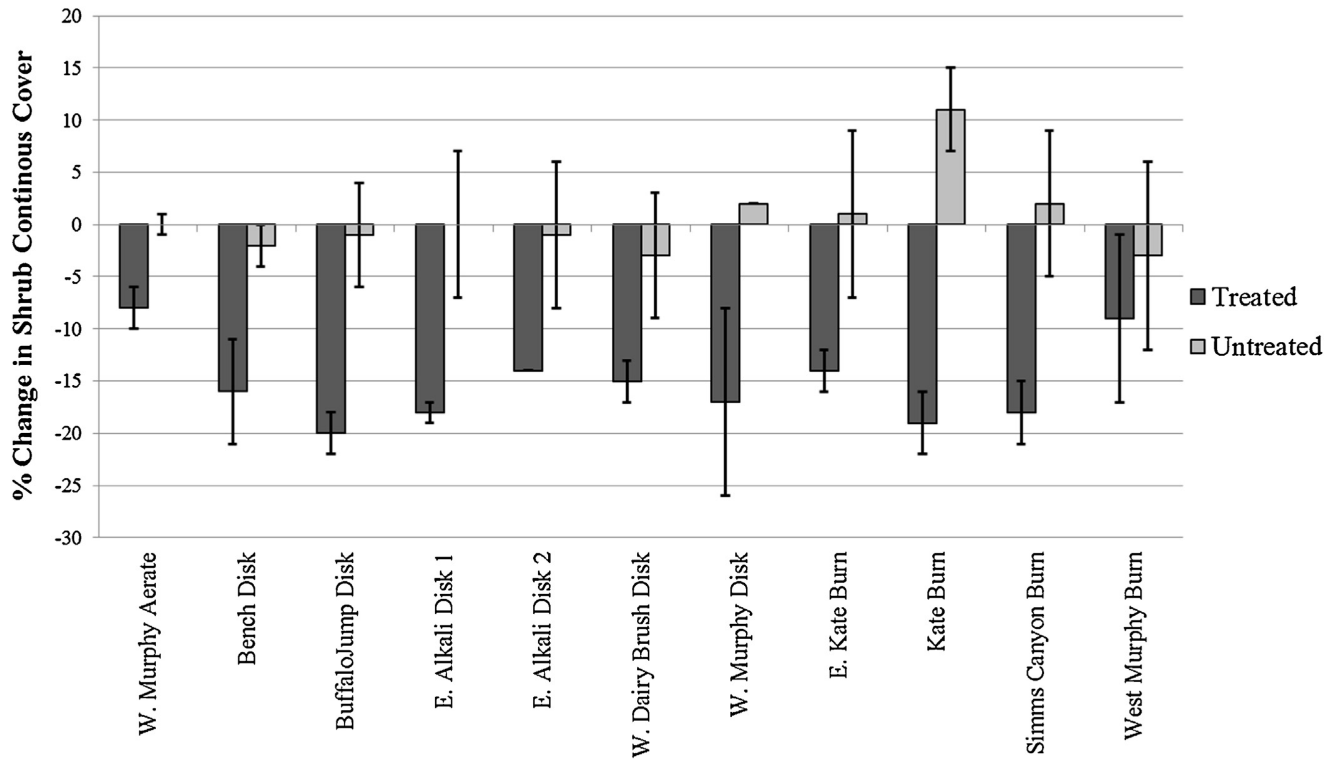

Fig. 6. Change in shrub cover detected using Landsat 30 m imagery for each of the sagebrush removal treatments. The average sagebrush cover of each site one year before treatment was subtracted from the average sagebrush cover post treatment. The same calculation was applied to adjacent untreated areas.

described in this paper provides spatially explicit information at all four geographic scales. The presence of sagebrush, bare ground, and herbaceous plants can be assessed over every square meter throughout the entire extent of sage-grouse habitat. Additionally, landcover classification projects like the Southwest ReGap (Lowry et al., 2007) can denote adjacent landcover types (e.g., juniper, agriculture, cheatgrass, etc.). This provides spatially explicit information of the availability, extent, and connectedness of sagebrush and other important habitat conditions (e.g., riparian areas, roads, and agriculture) for large geographic extents. It also defines the shelter and food availability at the site-scale that directly affects individual fitness, survival, and reproductive potential. This information can help guide policies, practices and support mitigation efforts in a cost effective manner.

5. Conclusion

The authors have demonstrated that the integration of high-resolution ground-based vertical imagery as enhanced ground samples with multiple scales of remotely sensed imagery can be used to effectively model cover components within sagebrush dominated landscapes. By assessing landscapes with high resolution imagery integrated with multiple scales of remotely sensed imagery, validated with traditional on-the-ground methods, the spatial and temporal limitations of traditional field-based rangeland monitoring can be mitigated. Spatial variation that cannot be addressed with point-based sampling is overcome by using high-resolution satellite based imagery. Temporal variation is overcome with yearly assessments from radiometrically calibrated imagery. This temporal ability helps evaluate long-term trends in percent cover and also provides better knowledge of the influence of annual weather patterns. This technique, applied across time, has potential to place cover change in a contextual perspective that has not been available before. In this way, past management practices can be evaluated for their effectiveness in altering rangeland percent cover and with this hindsight, improved management prescriptions can be developed.

Role of funding

The USDA NRCS Sage-Grouse Initiative had no role in the study design, collection, analysis, interpretation, or in writing the report.

Acknowledgements

The research was funded by the USDA NRCS Sage-Grouse Initiative. Data collected by Wildlife Federal Aid Project W-82-R was invaluable to the success of this research.

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