Detecting Dead Shrub Patches Using Remote Sensing Techniques in Southeast Idaho

Darci Hanson, GIS Training and Research Center, Idaho State University, Pocatello, ID 83209-8104, (http://giscenter.isu.edu, email: giscenter@isu.edu)

Keith T. Weber, GISP. GIS Director, Idaho State University. GIS Training and Research Center, 921 S. 8th Ave., Stop 8104, Pocatello, ID 83209-8104. webekeit@isu.edu

ABSTRACT

Five remote sensing satellite sensors (Hyperion [30m x 30m spatial resolution], Landsat 5 TM [30m x 30m spatial resolution], Satellite Pour l'Observation de la Terre (SPOT) 5 [10m x 10m spatial resolution], Quickbird [2.4m x 2.4m spatial resolution], and Worldview-2 [1.8m x 1.8m spatial resolution]) were used to determine if patches of dead-shrubs could be differentiated among a matrix of ground cover types (basalt, bare ground, grass, and live-sagebrush) using classification and regression tree analysis. Results for all image classifications were unsuccessful (overall accuracy < 75%) suggesting it may not be possible to detect dead-shrubs with the satellite-based sensors tested. However, pair-wise Analysis of Variance (ANOVA) results for *in situ* spectra collected with a handheld Analytical Spectral Devices, Inc (ASD) FieldSpec Pro field spectroradiometer, showed significant differences between dead-shrubs and all other ground cover types ($P < 0.001$). To aid in the characterization of vegetation at the study site and better understand the spectral signatures of landscape features, shrub height, age, and percent water content were also compared with ANOVA results indicating a difference in percent water content between live and dead-shrubs ($P < 0.001$).

KEYWORDS: Shrub die-off, shrub mortality, sampling, GIS, remote sensing, sagebrush, image classification

INTRODUCTION

Sage-grouse (*Centrocercus urophasianus*) are a sagebrush-obligate species requiring large, contiguous expanses of habitat (Connelly et al., 2004; Aldridge et al., 2008; Knick and Connelly, 2011). Some form (particularly big sagebrush (*Artemisia tridentata*) and silver sagebrush (*Artemisia cana*)) and quantity (~15-30% canopy cover) of sagebrush within the landscape are necessary to meet seasonal food, cover, and nesting requirements of sage-grouse (Patterson 1952, Connelly et al., 2000, Connelly et al. 2011, Knick and Connelly, 2011). While the quantity, or area, of available habitat is important so is habitat quality. The National Land Cover Database (NLCD) maps typically designate sagebrush dominated areas as shrub/scrub (Figure 1) and while the entirety of the NLCD land cover classification cannot be treated as viable sage-grouse habitat, the sage-grouse conservation area (SGCA) falls within a majority these areas (Connelly et al. 2004) (Figure 2; black boundary). Similarly, sage-grouse distribution closely mirrors sagebrush distribution (Figure 3) and for this reason, land managers may treat most shrub/scrub areas as viable sage-grouse habitat.

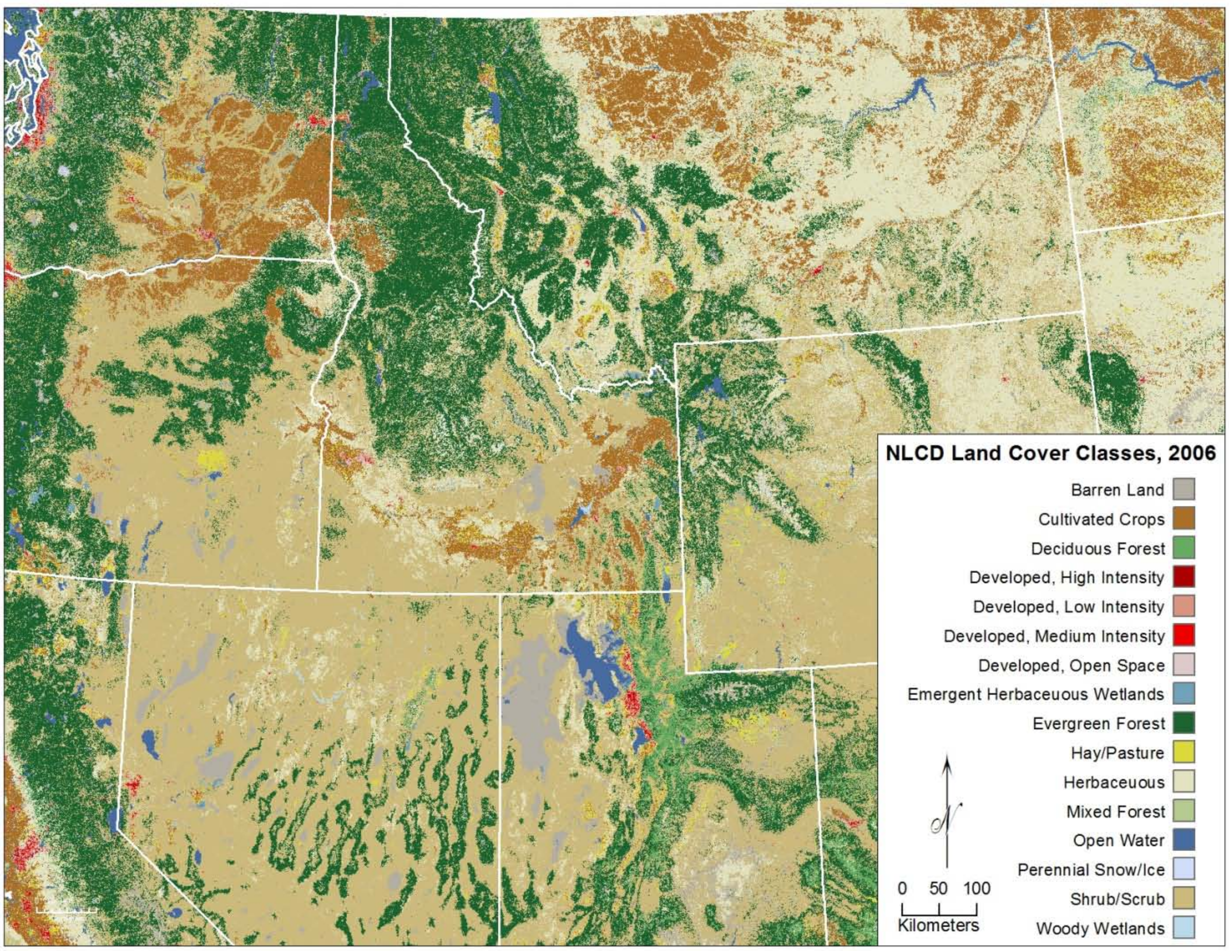

Figure 1. Land cover based upon the National Land Cover Database (NLCD) identifying areas of shrub/scrub land cover type, which land managers often delineate as sage-grouse habitat.

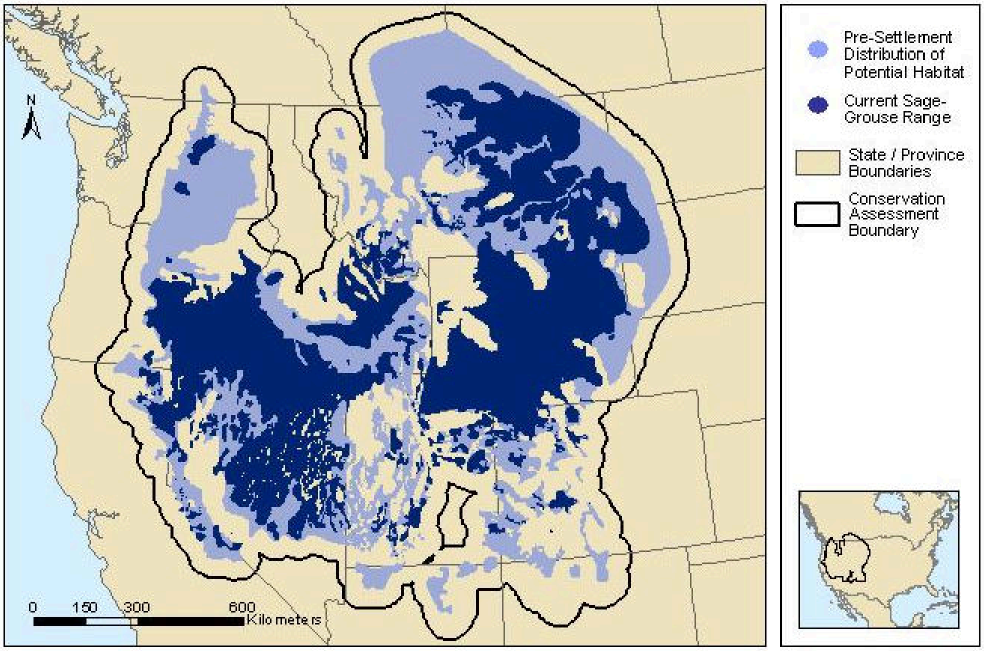

Figure 2. Sage-grouse conservation assessment boundary (SGCA) based on pre-settlement distribution of sage-grouse (source: Connelly et al. 2004).

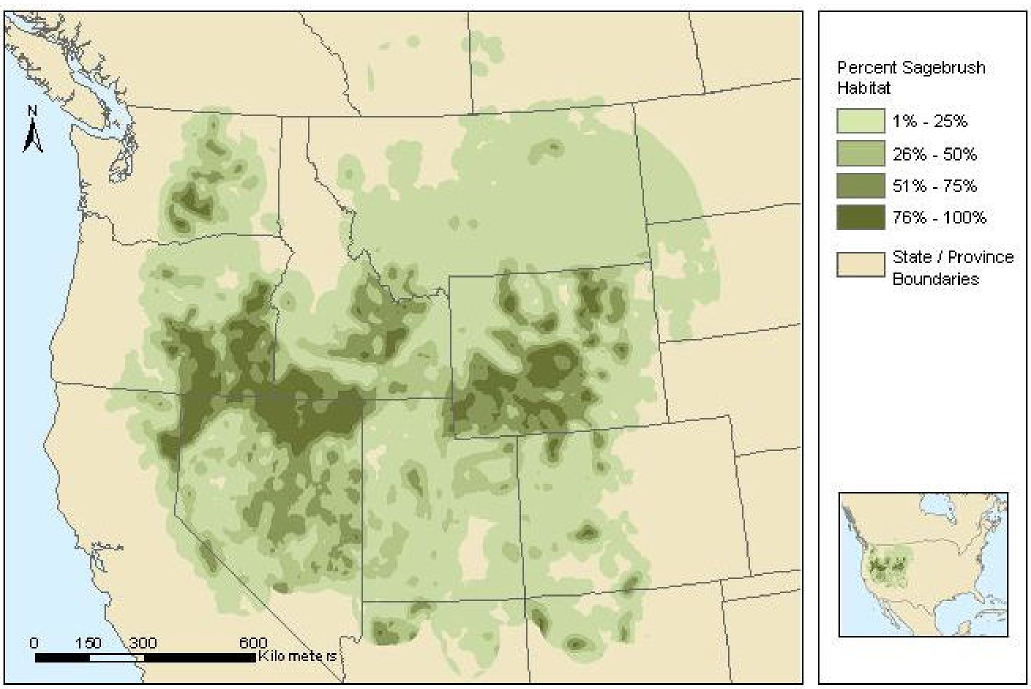

Figure 3. Estimated distribution of sagebrush density within the SGCA (source: Connelly et al. 2004).

Patches of shrub mortality can occur within otherwise healthy stands of sagebrush leading to an overestimation of total sage-grouse habitat. Sagebrush (shrub) mortality in semiarid rangelands was a widespread phenomenon in the salt-desert region of Utah between 1983 and 1988 due to persistent wet conditions (Wallace et al., 1989). In Wyoming, Colorado, and Utah snow-mold fungus was also indicated as a possible cause of shrub mortality (Hess et al. 1985). Though this phenomenon is known to occur throughout the semiarid sagebrush-steppe for a variety of reasons including drought, wetter than normal seasons, snow-mold fungus, and insects (Hess et al. 1985, Harper et al. 1989, Haws et al. 1989, Walser et al. 1989, Wiens et al. 1991, Tilley et al. USDA NRCS, Takahashi and Huntly 2010, Hampton and Huntly 2010), published reports pertaining to this phenomenon in southeast Idaho focus primarily on shrub mortality caused by leaf defoliating insects such as the Aroga moth (*Aroga websteri*). Sagebrush is the exclusive larval host of the Aroga moth and, in high numbers larva can kill host plants and reduce the production of foliage and flowering by surviving plants (Hampton and Huntly, 2010). Takahashi and Huntly (2010) reported increases in inflorescence growth (22%), flower production (325%), and seed production (1053%) after an experimental removal of insect herbivores from big sagebrush (*Artemesia tridentata*) plants with insecticide. Regardless of the cause, shrub mortality affects sage-grouse habitat as it impacts the primary source of food and shelter.

The ability to differentiate dead-shrubs from proximal targets with remote sensing imagery would allow land managers to better assess the quality of sage-grouse habitat across their distribution. Remote sensing systems onboard satellites provide high quality yet relatively inexpensive data, and are useful for monitoring a variety of landscape characteristics (Weber et al. 2008, Weber et al. 2009, Wheeler and Glenn 2003, McMahan et al. 2003, Sankey et al. 2008). A limitation of satellite-based sensors that can impact their ability to accurately record target radiance is the signal to noise ratio (SNR) of the sensor.

Atmospheric scattering and the signal to noise ratio (SNR) of a sensor can affect the accuracy of recorded radiance of a target at the sensor. Scattering occurs when reflected light strikes other particles in the atmosphere before reaching the satellite sensor. The type of scattering (Rayleigh, Mie, or Nonselective) is dependent upon the size of particles in the atmosphere, their abundance, the wavelength of the reflected light, and the depth of the atmosphere through which the energy is traveling (Campbell, 2008). Rayleigh scattering is attributed to atmospheric gas molecules and causes visible effects such as a blue sky. Mie scattering occurs when particles have diameters that are roughly equivalent to the wavelength of the scattered radiation, and is experienced primarily in the lower atmosphere through larger particles such as dust or pollen. Nonselective scattering accounts for what we observe as a whitish haze in the atmosphere, and refers to scattering that occurs from particles larger than the wavelength of the scattered light (Campbell, 2008). The SNR of a particular sensor can also influence the ability to accurately record reflected energy of a target. The signal refers to differences in image brightness caused by actual variations in scene brightness whereas noise refers to variations unrelated to scene brightness, and more with the inherent abilities of the sensor itself. If the magnitude of noise is large relative to the signal, the resulting image will not provide a reliable representation of the target of interest (Campbell, 2008). Because of these effects, compiling a spectral library characterizing *in situ* target spectra can be useful during classification of remotely sensed imagery.

Glenn et al. (2005) successfully detected leafy spurge occurrence in Swan Valley, Idaho using HyMap hyperspectral data collected by the HyVista. *In situ* spectra of leafy spurge and other proximal vegetation were collected using an Analytical Spectral Devices, Inc (ASD) FieldSpec Pro field spectroradiometer concurrent with image acquisition to characterize *in situ* target reflectance patterns at various wavelengths across the electromagnetic (EM) spectrum. Spectral profiles were combined with known geographic locations of leafy spurge to derive endmembers within images for two data collection years.

Characterization of *in situ* target spectra enabled visual analysis of minor variations in reflectance and absorption patterns of leafy spurge across the EM spectrum, while also serving to help the authors determine if a spectral subset of image data would be necessary for successful classification.

Williams and Hunt (2004) had success detecting leafy spurge occurrence in northeast Wyoming, near Devils Tower National Monument using Airborne Visible Infrared Imaging Spectrometer (AVIRIS) and spectral mixture analysis. *In situ* spectra of leafy spurge were collected with an ASD Fieldspec UV/VNIR Spectroradiometer, and were used to verify identification of spectral endmembers of leafy spurge. These positive results further illustrate how characterizing target spectra through field collection of *in situ* spectra can help achieve positive results during image classification.

Published reports pertaining to remote detection of shrub mortality is limited. Chopping et al. (2008) describe a new method for retrieving fractional cover of large woody shrubs at the landscape scale using Earth Observation System (EOS) Multiangle Imaging SpectroRadiometer (MISR) derived imagery and a hybrid geometric-optical canopy reflectance model. Stow et al. 2007 used very high spatial resolution (1m) multispectral imagery collected with an Airborne Data Acquisition and Registration (ADAR) system with visible near infrared (V/NIR) datasets to generate shrub cover change maps for Mission Trail Regional Park in San Diego, CA. Overall accuracy and kappa statistics for classification were 83% and 0.64 respectively.

The reflectance of an object over various wavelengths of the EM spectrum is commonly referred to as a spectral signature (Chuvieco and Huete 2010). Spectral signatures are initially recorded as radiance by the sensor that has been reflected by targets from a terrain. They are then converted to reflectance values to ease interpretation and to enable cross-comparison of remote sensing image data of an area from different dates. To reliably detect a feature using remote sensing, that feature must exhibit a unique spectral signature. It was hypothesized that a difference in plant water content between dead-shrubs and live-sagebrush might be a key factor for successful classification of dead-shrub. There is a strong relationship between the reflectance in the shortwave infrared (SWIR) (1550 – 1750 nm and 2080 – 2350 nm) and the amount of water present in the leaves of a plant canopy (Jensen, 2007). Water in plants absorb incident energy in this region with increasing strength at longer wavelengths.

To detect, and thereby characterize the extent of shrub mortality within sage-grouse habitat areas of southeast Idaho, remote sensing technologies were applied. This paper describes the field sampling performed during the summer of 2010 as well as laboratory analysis of image data from five remote sensing satellite-based sensors, to determine if patches of dead-shrubs could be detected among the matrix of ground cover types at the O'Neal Ecological Reserve, Idaho. This study used random, adaptive, and directed sampling techniques to collect various sagebrush plant characteristics including field and laboratory measured weights of twig samples from dead-shrubs and live-sagebrush to calculate percent water content, along with a plot level determination of homogeneity. These data were used to classify imagery for presence/absence of dead-shrubs. Vegetation data were collected to determine if there was a statistical difference in percent water content between dead-shrubs and live-sagebrush, and likewise, if a difference in percent water content would translate to spectral differentiation in the SWIR region of the EM spectrum.

METHODS

Study area

The O'Neal Ecological Reserve (Figure 4) is located along the Portneuf River, approximately 30 km southeast of Pocatello, Idaho (42° 42' 25"N, 112° 13' 0" W). The O'Neal receives <0.38 m of precipitation annually with nearly 50 percent falling as snow in the winter months (October 1- March 31). An average of 0.15 m (SE = 55.4) of rainfall occurs during the growing season (April 1 – September 31). The topography is relatively flat with a mean elevation of approximately 1426 m (1400-1440 m). The site is characterized by shallow, well drained soils over basalt flows originally formed from weathered basalt, loess, and silty alluvium that remain homogenous throughout the site (USDA NRCS 1987, Weber and Gokhale 2010). Dominant plant species include big sagebrush (*Artemesia tridentata*) with various native and non-native grasses, including Indian rice grass (*Oryzopsis hymenoides*) and needle-and-thread (*Hesperostipa comata*) (Davis and Weber, 2010). The O'Neal is managed by Idaho State University (ISU) while land immediately surrounding it is managed by the USDI BLM. This area has a history of rest-rotation cattle grazing (> 20 years) at low stocking rates (300 AU/ 1467 ha [6 AUD ha-1]). The last fire to occur within the O'Neal was in 1992.

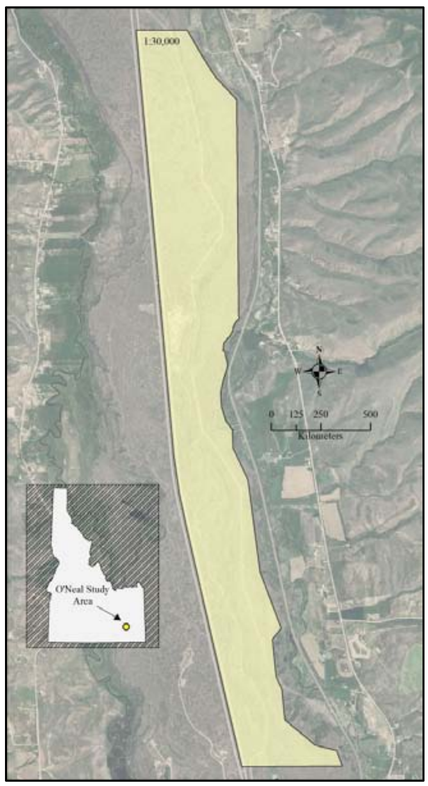

Figure 4. Study area: The O'Neal Ecological Reserve, represented by the polygon, is located near McCammon, Idaho, 30km south of Pocatello. This was the study area was chosen as part of a research project attempting to remotely detect dead-shrub patches using five satellite-based sensors (Hyperion, Landsat 5 TM, SPOT-5, Quickbird, and Worldview-2)

Field data collection

Two sampling sessions were completed during the summer of 2010. The first session (14 June 2010 – 25 June 2010) consisted of 60 randomly located sample points followed with adaptive sampling applied to stands determined to be homogeneous (> 50%) for dead-shrub based on protocols described at http://giscenter.isu.edu/research/Techpg/nasa_postfire/results.htm.

Sample points were navigated to using a Trimble GeoXH GPS receiver (< 1.0 m @ 95% CI following post-process differential correction) with each point referred to as plot center. An insufficient number of dead-shrub sites were found during the initial sampling session (n = 13) and as a result, a directed sampling approach was used in the second sampling session (29 June 2010 – 14 July 2010). The directed sampling approach is one where field personnel use their knowledge of the study area to locate additional sample sites. While this approach introduced a bias into the sample dataset it was effective for locating uncommon targets such as homogeneous stands of dead-shrubs. When a new site was located, the same sampling protocol as described above was followed. The goal of the field collection campaign was to collect a minimum of 60 live-sagebrush and 60 dead-shrub sites.

Sagebrush and dead-shrub twig samples were collected from up to four plants at each site and weighed using a Pesola scale (+/- 1 g). Selected twigs were approximately 5 mm in diameter and approximately 250 mm in length. A total of 30 live-sagebrush twig samples were collected as well as 30 dead-shrub twig samples. These samples were placed in a bag, labeled with a unique ID consisting of the sample point ID, date, and sequence (1-4) and returned to the laboratory for drying and determination of percent water content (Davis et al. 2011).

Field spectra were collected from five *in situ* target types (basalt, bare ground, grass, dead-shrub, and live-sagebrush) during summer, 2010 (n = 2,565). Data were collected using the ASD FieldSpec Pro and imported into Microsoft Excel for further processing. Spectra were sorted by target and wavelength.

Image acquisition and processing

Imagery for the O'Neal study area was collected during the summers of 2009-2010 to capture peak greenness of sagebrush in southeast Idaho. This was determined by viewing time-lapse video of sagebrush at the O’Neal from 12 March 2010 through 10 October 2010 (URL here for that file) (Table 1).

Table 1. Remote sensing satellite imagery collected for the O’Neal Ecological Reserve, Idaho May - July, as part of a research project to remotely detect dead-shrub patches using five satellite-based sensors (Hyperion, Landsat 5 TM, SPOT-5, Quickbird, and Worldview-2).

Sensor	Collection Date	Spatial Resolution	Spectral Resolution
Hyperion	16 June 2010	30m x 30m	220 bands: 400 nm to 2500 nm
Landsat 5 TM	07 May 2010	30m x 30m	7 bands: Blue, Green, Red, NIR, SWIR 1. SWIR 2
SPOT 5	20 June 2010	10m x 10m	4 bands: Green, Red, NIR, SWIR
Quickbird	06 June 2009	2.4m x 2.4m	4 bands: Blue, Green, Red, NIR
Worldview-2	16 May 2010	1.8m x 1.8m	8 bands: Blue, Green, Red, NIR1, NIR2 Coastal Blue, Yellow, Red Edge

All satellite imagery (excluding Hyperion) were atmospherically corrected using Idrisi Taiga (ver. 16.04) image processing software. Images (excluding Landsat) were co-registered for improved horizontal positional accuracy. Landsat data were delivered registered to a high degree of accuracy, however to confirm registration accuracy, data were compared against 2004 National Agricultural Imagery Program (NAIP) imagery (1m x 1m spatial resolution) (horizontal positional accuracy within +/- 5m). WV-2 and Quickbird imagery were co-registered to known ground control points of high positional accuracy (Weber et al., 2010[b]). Due to coarse pixel resolution, it was not possible to co-register Hyperion, Landsat, and SPOT imagery to the same ground control points used for WV-2 and Quickbird, therefore images were co-registered to the 2004 NAIP imagery. Root mean square error (RMSE) was <50% (Table 2) of the pixel resolution for all co-registered imagery, which is suggested as the minimum necessary for reliable classification (Weber, 2006).

Table 2. Co-registration results for remote sensing satellite imagery collected over the O'Neal Ecological Reserve, Idaho

Sensor	Spatial Resolution (mpp)	RMSE	% pixel size
Hyperion	30.0	2.76m	9
Landsat	30.0	2.97m	10
SPOT	10.0	1.68m	17
Quickbird	2.4	0.07m	3
WV-2	1.8	0.10m	6

Spectral signatures were extracted for all images in Idrisi (Image Processing→Signature Development→SEPSIG) and spectral differentiability was tested using the Transformed Divergence Index. Transformed divergence is a commonly used measure of differentiability that calculates the statistical "distance" between classification categories. The calculated differentiability value provides a measure of potential classification accuracy. With a multiplier constant of 2,000, a calculated value of 1,500 is the suggested threshold for significant differentiability (Richards 1993, Lillesand and Kiefer 2000).

Supervised classification of imagery was performed in Idrisi to differentiate dead-shrub classes from live shrub classes using 119 field sample points acquired during the summer field sampling sessions. Sample points were separated into two classes where an attribute of 1 indicated dead-shrub and 2 indicated "other" (e.g., live-shrub, grasses, bare ground, or basalt). Using Hawth's Tools (Beyer, 2004) in ArcMap 9.3.1, these sample points were randomly selected and divided into training and validation sites to allow for independent validation. Using Idrisi a presence/absence model for dead-shrubs was created using classification and regression tree analysis (CTA) (Image Processing→Hard Classifiers→CTA). Classification and regression tree analysis is a non-probabilistic, non-parametric statistical technique that is adept at modeling data that is non-normally distributed (Breiman et al. 1998; Friedl and Brodley 1997; Lawrence and Wright 2001; Miller and Franklin 2001). It is hypothesized that dead-shrub patches are non-normally distributed and for this reason, may be modeled more accurately with CTA relative to other supervised classification techniques such as maximum likelihood, which may be more appropriate when a dataset is known to follow a certain distribution pattern (Clark Labs, 2008). The CTA algorithms select useful spectral and ancillary data which optimally reduce divergence in a response variable (Lawrence and Wright 2001). CTA uses machine-learning to perform binary recursive splitting operations and ultimately yields a classification tree diagram that is used to produce a model of the response variable. Splitting algorithms common to CTA include entropy, gain ratio, and Gini. The entropy algorithm has a tendency to over-split, creating an unnecessarily complex tree (Zambon et al., 2006). The gain ratio algorithm addresses the over-splitting problem through normalization while the Gini algorithm partitions the most homogeneous clusters first using a measure of impurity while isolating the largest homogeneous category from the remainder of the data (McKay and Campbell 1982; Zambon et al., 2006). As a result, classification trees developed using the Gini splitting algorithm are less complex and therefore more easily understood by the analyst. For these reasons, the Gini splitting algorithm was selected for use in this study.

A key advantage of CTA is its ability to use both spectral and non-spectral data selectively during the splitting and classification process. This allows for the use of topographic data which may be equally important in modeling dead-shrub. Such ancillary data can be used with other supervised classification techniques (Lillesand et al., 2008) but classifiers like maximum likelihood use all input data to arrive at a final classification. This is in contrast to the advantage of CTA noted above, which selectively applies input data in its classification process.

All atmospherically corrected multispectral imagery bands and an NDVI layer were used for the classification. For Hyperion, 61 image bands were selected from 220 as part of a standard data reduction technique along with three derivative slope bands for image classification. These bands were selected to correspond with wavelengths determined through visual analysis of graphed *in situ* spectra as optimal for detection of dead-shrub patches based on mean reflectance peaks of dead-shrub spectra and areas of non-overlapping variability for target spectra.

Normalized Difference Vegetation Index (NDVI) is an index of photo-synthetically active vegetation and is calculated using the red and near infrared (NIR) bands of multispectral imagery. The resulting NDVI has an interval of -1 to +1, where -1 is no vegetation and +1 is pure photo-synthetically active vegetation (Rouse et al., 1973, Tucker 1979). High reflectance of vegetation in the NIR wavelengths due to spongy mesophyll within leaf structure makes NDVI a very useful landscape productivity parameter in its ability to highlight areas of photo-synthetically active vegetation. Though there has been some evidence that NDVI is less successful a predictor variable in study areas where bare-soil exceeds 20% (Sankey et al. 2009), it is still widely accepted to be useful as a predictor variable for vegetation and is used in rangeland studies (Weber et al. 2009, Gokhale and Weber. 2009, Blanco et al. 2007, Aldridge and Boyce 2007, Zou et al. 2006). NDVI was included in this study for all multispectral imagery, as an additional separation measure of dead-shrub and was calculated in Idrisi Taiga image processing software following equation 2. The inclusion of this measure helped to isolate actively photosynthesizing vegetation from senesced vegetation.

$$NDVI = \frac{NIR\ Band - Red\ Band}{NIR\ Band + Red\ Band} \text{ (Eq. 2)}$$

Laboratory and statistical analysis

Twig samples were dried in ovens at 80° Celsius for 48 hours. Once dried, samples were re-weighed using the same Pesola scale used to weigh them in the field. Field weights were defined as “wet weight” and post-drying laboratory weights as “dry weights.” Wet and dry weights were recorded in MS Excel. Percent water content was calculated following equation 3. A single factor ANOVA test was used to determine if there was a difference in percent water content between live-sagebrush and dead-shrubs.

Percent Water Content = 1 – (dry weight/wet weight) (Eq. 3)

Descriptive statistics for *in situ* spectra were calculated, and mean reflectance values for each target type were graphed creating a spectral profile of each target type. Variability of reflectance (@ 95% CI) within each target spectra was calculated by multiplying the standard error by 1.96 (or the z-score for a 95% confidence interval). These values were then applied to the calculated mean of each target at each wavelength and graphed. Targets were considered differentiable when separated by > 1.96 standard error. Pair-wise single factor ANOVA tests were performed (basalt, bare ground, grass, and live-sagebrush) to determine if dead-shrubs could be differentiated from the matrix of other rangeland features.

Derivative spectroscopy, or derivative analysis, is a tool commonly used in the analysis of hyperspectral remote sensing data. Derivative techniques enhance minute fluctuations in spectral reflectance and may help separate closely related absorption features (Louchard et al., 2002). Spectral derivative techniques have been applied in remote sensing and found to eliminate background signals and differentiate overlapping signatures. When applied to remote sensing, derivative analysis is a measure of the slope of the line of a portion of the spectral profile where the slope of the line appears to differ among target types. For the purpose of this research this technique was used as an additional separation measure for classification of dead-shrub using Hyperion hyperspectral imagery.

Spectral profiles were analyzed visually to locate points where the slope of the line appeared to differ from the slopes created by the other targets within the same waveband region. Derivative slopes were calculated in Idrisi using the Hyperion imagery for three spectral regions using the following equation (Tsai and Philpot 1998):

$$\text{Slope} = \frac{s(\lambda_i) - s(\lambda_j)}{\Delta\lambda} \text{ (Eq. 3)}$$

Where $s(\lambda_i)$ is the reflectance at wavelength *i*, $s(\lambda_j)$ is the spectral reflectance at wavelength *j*, and $\Delta\ \lambda$ refers to difference between wavelengths *i* and *j*.

Classification accuracy assessment

Resulting classification layers were independently validated in Idrisi (Image Processing→Accuracy Assessment→ERRMAT) using a standard error matrix and Kappa statistic, where predicted (modeled) target type (e.g., dead-shrub) locations were compared against known (field) target type (e.g., dead-shrub) locations (Table 3). The Kappa index of agreement served as an indicator of how well the classification performed relative to a random classification. Classifications with ≥ 75% overall accuracy were considered reliable (Goodchild et al., 1994, Weber 2006). However, classifications with overall accuracy of ~ 70% were still considered positive results. Paired error matrix tests of significance (Congalton and Green, 2008) were used to determine if any of the image classifications performed statistically better than any other, where the null hypothesis (0) indicates no difference between classifications.

RESULTS AND DISCUSSION

Field data

Of the sample points collected 97.7% were post-process differentially corrected to < 1m, while 0.002% were corrected at an accuracy > 1m. Sub-meter accuracy of field locations resulted in a high degree of horizontal positional accuracy which ensured that field locations were reliably located in the correct pixel during image classification. For high spatial resolution remote sensing imagery such as Quickbird (2.4m spatial resolution) or Worldview-2 (1.8m spatial resolution) a high degree of horizontal positional accuracy (RMSE < 50%), because if the target being classified comprises one pixel of that imagery, a slight shift in the actual location relative to the measured field sites can result in lower overall accuracy (Weber 2006, Weber et al. 2007).

Image processing

Transformed divergence values for each of the spectral signatures developed for this study were well below the threshold (1500; Table 4) indicating low potential for differentiation of dead-shrub from the matrix of other targets during image classification.

Table 4. Transformed divergence values for five remote sensing satellite images (Hyperion, Landsat 5 TM, SPOT 5, Quickbird, and Worldview-2) testing spectral separability of dead-shrub patches using the SEPSIG tool in Idrisi Taiga image processing software as part of a research project attempting to remotely detect dead-shrub patches at the O'Neal Ecological Reserve, Idaho.

	Sensors				
Transformed	**Hyperion**	**Landsat**	**SPOT**	**Quickbird**	**WV-2**
Divergence Values	840.82	563.77	826.64	952.57	605.96

Laboratory and statistical analysis

The mean percent water content of live-sagebrush plants was 64.6% (SE = 0.01; n = 30) and 15.6% for dead-shrubs (SE = 0.03; n = 30) and ANOVA results indicated a significant difference (P < 0.001) (Davis et al., 2010). These results suggest there is a difference in water content between dead-shrub and live-sagebrush, which means that dead-shrub patches should exhibit greater reflectance values in the SWIR region of the EM spectrum relative to live-sagebrush which would experience greater absorption at these wavelengths. These results support the hypothesis that a spectral band sensitive to the SWIR region may be important for successful classification of dead-shrubs.

Pair-wise single factor ANOVA tests for differentiability between ASD field spectra of dead-shrub and the other *in situ* targets (basalt, bare ground, grass, and live-sagebrush) revealed a statistical difference between all paired samples (P < 0.001). Calculated variability of spectra within each target class was narrow (spectral separation > 1.96 SE) further supporting evidence for differentiability among target spectra (Hanson et al., 2010). This indicates that dead-shrub patches have a unique spectral signature (the unique combination of reflected and absorbed EM radiation at varying wavelengths that uniquely identifies a target) relative to the other target types used in this study (basalt, bare ground, grass, and live-sagebrush), and therefore may be detectable via a remote sensing platform.

Three points of slope deviation were found among the mean *in situ* target spectra. These line-segments were found between 700 nm and 730 nm, 1115 nm and 1140 nm, and 1290 nm and 1330 nm (Figure 5). The resulting slopes were selected as they are considered fundamentally diagnostic (Becker et al. 2005). Slopes of these line-segments were calculated using Hyperion bands 38 and 35, 97 and 99, and 115 and 118 respectively following equation 3.

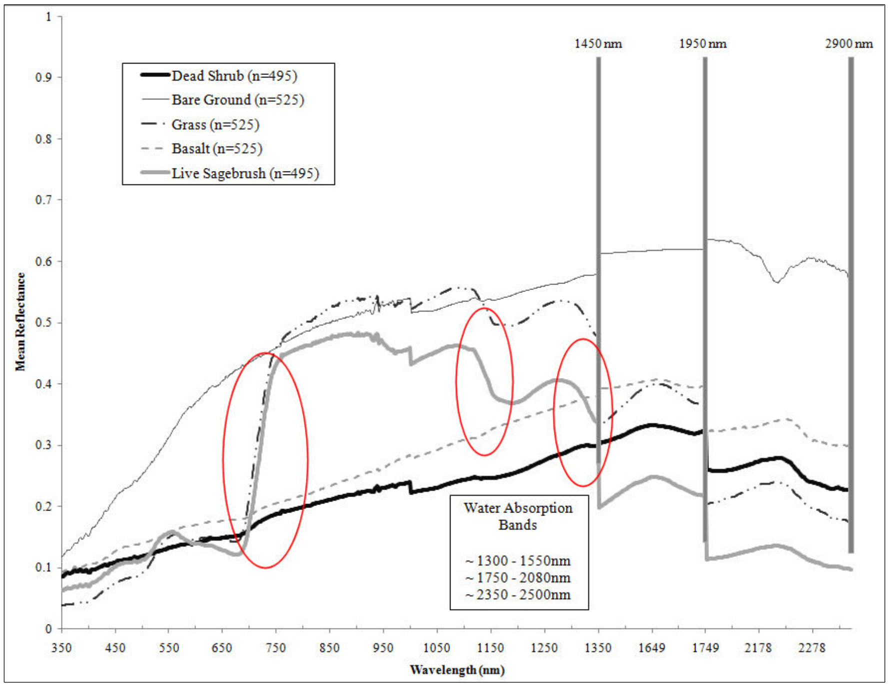

Figure 5. Points of slope deviation among mean *In situ* target spectra (basalt, bare ground, grass, dead-shrub, and live-sagebrush) collected at the O'Neal Ecological Reserve, Idaho.

The spectral profiles were superimposed with representations of the image bands for each sensor included in this study to gain insight as to which bands might be useful for classification (Figures 6 through 9). Visual analysis of these data revealed the reflectance peaks for dead-shrub spectra were consistently different from other target spectra between 700 nm and 2500 nm. Image bands for Hyperion were not superimposed with the spectral profiles because the excessive number of available bands (220) and narrow band widths characteristic of hyperspectral data resulting in near continuous spectral coverage. The bands that appeared to show the greatest difference between dead-shrub spectra and other targets for each of the sensors were: NIR, SWIR-1, and SWIR-2 for Landsat 5 TM (Figure 6); NIR and SWIR for SPOT 5 (Figure 7); NIR for Quickbird (Figure 8); and red edge (RE), NIR-1 and NIR-2 for WV-2 (Figure 9).

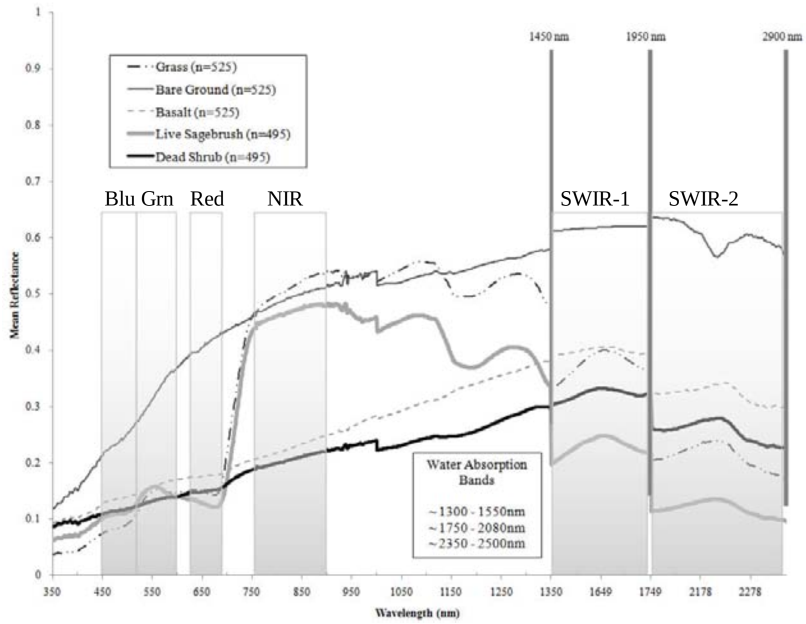

Figure 6. Landsat 5 TM image bands superimposed with plotted mean reflectance of *in situ* target spectra collected at the O'Neal Ecological Reserve, Idaho as part of a research project attempting to remotely detect dead-shrub patches using five satellite-based sensors (Hyperion, Landsat 5 TM, SPOT-5, Quickbird, and Worldview-2) This graph was used as a pre-analysis tool to get an idea of which bands might be useful during image classification for the successful identification of dead-shrub patches.

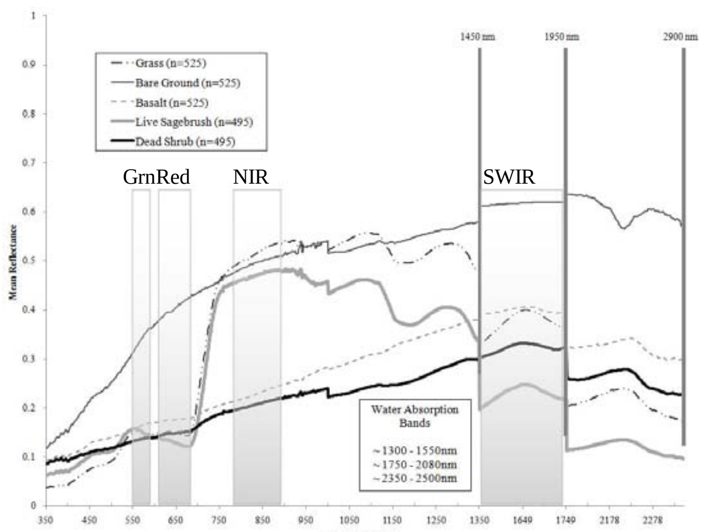

Figure 7. Spot 5 image bands superimposed with plotted mean reflectance of *in situ* target spectra collected at the O'Neal Ecological Reserve, Idaho as part of a research project attempting to remotely detect dead-shrub patches using five satellite-based sensors (Hyperion, Landsat 5 TM, SPOT-5, Quickbird, and Worldview-2) This graph was used as a pre-analysis tool to get an idea of which bands might be useful during image classification for the successful identification of dead-shrub patches.

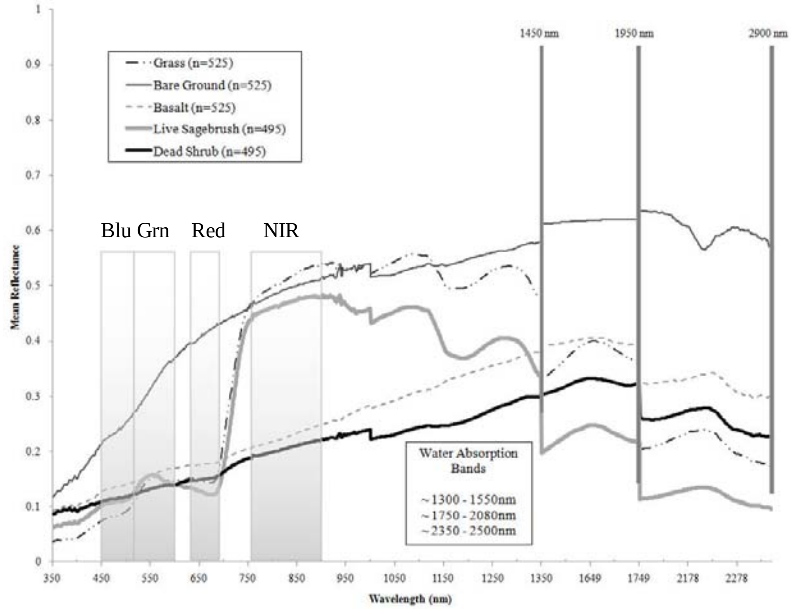

Figure 8. Quickbird image bands superimposed with plotted mean reflectance of *in situ* target spectra collected at the O'Neal Ecological Reserve, Idaho as part of a research project attempting to remotely detect dead-shrub patches using five satellite-based sensors (Hyperion, Landsat 5 TM, SPOT-5, Quickbird, and Worldview-2) This graph was used as a pre-analysis tool to get an idea of which bands might be useful during image classification for the successful identification of dead-shrub patches.

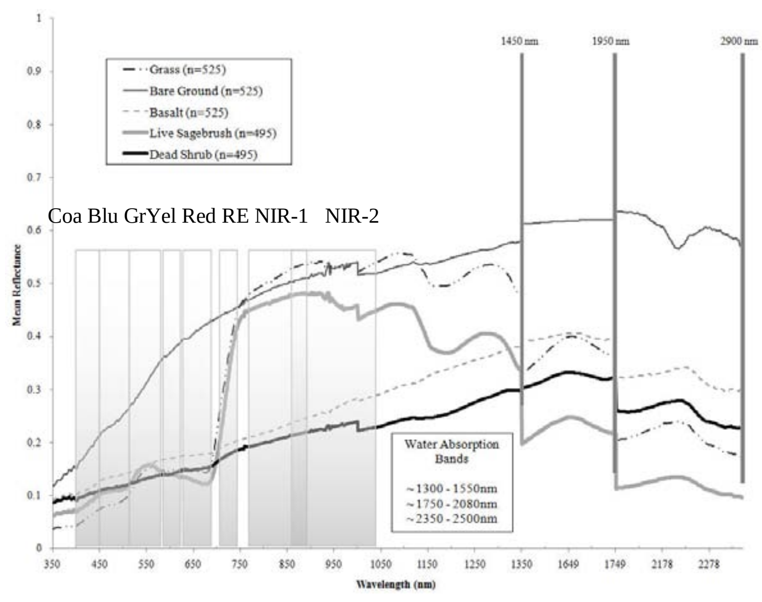

Figure 9. Worldview-2 image bands superimposed with plotted mean reflectance of *in situ* target spectra collected at the O'Neal Ecological Reserve, Idaho as part of a research project attempting to remotely detect dead-shrub patches using five satellite-based sensors (Hyperion, Landsat 5 TM, SPOT-5, Quickbird, and Worldview-2) This graph was used as a pre-analysis tool to get an idea of which bands might be useful during image classification for the successful identification of dead-shrub patches.

Classification accuracy assessments

Image classification of dead-shrub was unsuccessful regardless of the sensor used for classification (overall accuracy < 75%) (Table 5). This is consistent with results achieved with the transformed divergence measure of separability test. Overall Kappa statistics were also low, indicating classifications were only slightly better than random. Paired error matrix tests of significance suggest no image classification performed better than any other ($Z < 1.96$). As a result, we conclude that detection of dead-shrubs is not possible with the sensors used in this study.

Table 5. Classification accuracy assessment for the classification of five remote sensing satellite images (Hyperion, Landsat 5 TM, SPOT 5, Quickbird, and Worldview-2) of dead-shrub patches at the O'Neal Ecological Reserve, Idaho. This was part of a research project testing the abilities of satellite-based sensors to detect sage-grouse habitat quality.

	Hyperion	Lands 5 TM	SPOT 5	Quickbird	WV-2
Users Accuracy	55 %	65 %	67 %	58 %	62 %
Producers Accuracy	60 %	65 %	60 %	64 %	66 %
Overall Accuracy	54 %	66 %	65 %	59 %	61 %
Kappa	10 %	32 %	29 %	18 %	23 %

Assesement of error and bias

There are several possible factors that could have contributed to the negative results for this study. Worldview-2 is the finest spatially resolved multispectral remote sensing satellite currently available. Despite its spatial resolution, this imagery may not be sufficiently spatially resolved for the type of classification attempted. Though an effort was made to record stands that represented homogenous pixels of either live-sagebrush or dead-shrubs, there likely was some pixel mixing of target spectra with adjacent or underlying targets such as exposed soil or grass which may overpower or alter the resulting dead-shrub spectra recorded at the sensor. Sagebrush is a woody shrub species and its associated spectral signature, like most vegetation in semiarid regions, lacks significant spectral contrast compared to features with strong reflectance like soil (Okin et al., 2001). Soil albedo often produces a much higher reflectance than other targets and, lacking leaves, dead-shrubs may allow underlying soil to be exposed to the sensor.

SNR of a sensor can further impact recorded radiance of a target at the sensor as it refers to the inherent abilities of the sensor to accurately record data. An SNR of approximately 100:1, as with the Hyperion imagery (Boardman, 2002) used in this study, is low, which could help explain the negative classification results observed for this sensor.

Laboratory results suggest a statistical difference in plant percent water content between dead and live shrubs ($P < 0.001$). However image classifications of dead-shrub were negative for all sensors tested. These results do not support the hypothesis that a SWIR band would enable differentiation of dead-shrub patches however these results are more likely the result of the relatively coarse spatial resolution of the sensors containing SWIR image bands (Landsat, SPOT, and Hyperion). Additionally, the spectral profile produced by bare ground demonstrated nearly identical absorption and reflectance patterns as dead shrub, though with higher reflectance. It is possible that negative classification results were due to the inability of the sensor to differentiate dead shrub reflectance from the very similar yet overpowering bare ground reflectance. Future research might reexamine this hypothesis using different sensors with finer spatial resolution, as results of pair-wise ANOVA tests between *in situ* spectra of dead-shrub and proximal targets (basalt, bare ground, grass, and live-sagebrush) indicate that differentiation was possible ($P < 0.001$ for all sampled pairs), however while *in situ* proved that dead shrub-spectra had higher reflectance in the SWIR region than live-sagebrush, dead-shrub spectra was consistently lower than most other target types, including bare ground.

Spectral resolution of each sensor is yet another consideration. Imagery with higher spectral resolution can enable discrimination of subtle differences in spectral signatures (Aspinall et al., 2002), and provide increased species discrimination (Glenn et al., 2005). In this study, the image classification of dead-shrubs with the Hyperion hyperspectral sensor was unsuccessful despite a high spectral resolution (220 spectral bands). Although spatial resolution for Hyperion is coarse (30m x 30m) and SNR is poor (< 100:1) (Boardman, J., 2011) which could affect the sensor's ability to accurately record target radiance even with improved spectral resolution.

CONCLUSIONS

This project attempted to differentiate shrub mortality by classifying imagery from five satellite-based sensors (Hyperion, Landsat 5 TM, SPOT, Quickbird, and Worldview-2). Classification results were unsuccessful, with users' accuracies ranging from 55% to 67%, producers' accuracies ranging from 60% to 66%, and overall accuracies ranging from 54% to 66%. Paired error matrix tests of significance determined that no image classification performed better than any other ($Z < 1.96$). These negative results were likely due to a combination of factors including coarse spatial resolution, pixel mixing, low spectral resolution, or poor SNR of the sensor. Future research should revisit this study with sensors other than the five tested here.

Analysis of *in situ* spectra, collected concurrent with the field season described in this study, confirmed differentiability of dead-shrub spectra ($P < 0.001$) from the matrix of other targets (basalt, bare ground, grass, and live-sagebrush), though spectral profiles produced by dead-shrub and bare ground demonstrated nearly identical reflectance and absorption patterns, and dead-shrub spectra had consistently lower reflectance than bare ground. In addition a difference was found in plant percent water content between dead and live shrubs ($P < 0.001$) suggesting that differentiation might be possible with sensors possessing SWIR band(s). Dead-shrub classifications with the imagery used in this study containing SWIR bands (Landsat, SPOT, and Hyperion) were unsuccessful and this may be due to the relatively coarse spatial resolution and resulting pixel mixing among other contributing factors. Additionally, while analysis of *in situ* spectra proved that dead-shrub spectra had higher reflectance in the SWIR region than live-sagebrush, dead-shrub spectra were consistently lower than most other target types, including bare ground.

It is hypothesized that successful classification may be possible with sensors possessing very high spatial, spectral, and radiometric resolutions. These stipulations will reduce pixel mixing, increase sensitivity of the sensor to a wider range of wavelengths across the EM spectrum, and increase the ability of the sensor to discriminate between differences in signal strengths as it records radiant flux. Currently, the required spatial resolution is only available using aerial photography. However, unlike satellite sensors where the entire image footprint is effectively acquired from a near nadir (directly underneath the sensor) perspective, with airborne sensors an increasing off-nadir angle exists for pixels at or near the edge of the imagery. Technology is constantly and rapidly evolving however, and if a satellite-based sensor is developed incorporating very high spatial, spectral, and radiometric resolutions, results from this study suggest that positive detection of dead-shrub patches may be possible.

Globally, shrublands are one of the least protected biomes, having undergone conversion to agriculture or invasion by exotic plant species (Brooks et al., 2004, Knick and Connelly, 2011). In the west, loss of shrublands has led to population declines for shrubland obligate species, such as sage-grouse (Peterjohn and Sauer 1999, Vickery et al., 1999, Brennan and Kuvlesky 2005, Askins et al., 2007). As land managers work towards developing conservation measures for sage-grouse, any additional information regarding the quality of sage-grouse habitat could prove useful. Remote detection of shrub mortality within otherwise live and healthy stands of sagebrush could be one such piece of additional information. Though negative classification results were achieved with this study, results of *in situ* spectral analysis imply that separation is possible. Additional research using more highly resolved sensors is merited.

ACKNOWLEDGEMENTS

This study was made possible by a grant from the National Aeronautics and Space Administration Goddard Space Flight Center (NNX08AO90G). Idaho State University would also like to acknowledge the Idaho Delegation for their assistance in obtaining this grant.

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Recommended citation style:
Hanson, D. and K. T. Weber, 2011. Detecting Dead Shrub Patches Using Remote Sensing Techniques in Southeast Idaho. Pages 211-234 in K. T. Weber and K. Davis (Eds.), Final Report: Assessing Post-Fire Recovery of Sagebrush-Steppe Rangelands in Southeastern Idaho. 252 pp.

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