FINAL REPORT:
FORECASTING RANGELAND CONDITION WITH GIS IN SOUTHEASTERN IDAHO
(NNG06GD82G)

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Project web-site: http://giscenter.isu.edu/research/techpg/nasa_oneal/template.htm

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FORECASTING RANGELAND CONDITION WITH GIS IN SOUTHEASTERN IDAHO

Executive Summary
Significant Findings and Achievements

- The credibility of all geospatial models rests upon the model's correspondence with the real-world. All too often however, GIS and remote sensing techniques are being used to develop models that have few similarities to conditions found in the field. In an effort to pursue rapid publication some scientists have evidently overlooked ground validation and opted instead to correlate their results with the results of another model that was previously published in a respected journal. Scientists at Idaho State University's GIS Training and Research Center (GIS TReC) have never lost sight of the importance of validation, and all models described in this final report include robust error assessment and validation with pertinent field data. Furthermore, these field data are well documented (cf. chapters 1-5) and are made readily available to the scientific community and the general public through the GIS TReC's website (http://giscenter.isu.edu/ research/techpg/ nasa_oneal/results.htm).

- Understanding and reporting error and bias is critical to the proper and ethical use of geospatial technologies as a decision support tool. We investigated the effect of geo-reference and co-registration errors using ground control platforms, surveyed locations (+/- 1 cm horizontal positional accuracy), and high spatial resolution aerial imagery (0.15mpp). The results of this effort (cf. chapter 6) allowed researchers to quantitatively address co-registration error using an ingenious use of inexpensive blue-tarps and QuickBird satellite imagery. The results of this study demonstrate that accurate co-registration between field sites and satellite imagery can increase producer's accuracy substantially (e.g., from 37.5% to 100% accuracy as shown in the study detailed in chapter 12).

- One student who completed his MS thesis under this grant, Mansoor Raza, documented a bias in aerial photograph interpretation by investigating the agreement between cover type determinations made at three high spatial resolutions (0.15, 0.30, and 1.0 mpp). His results (cf. chapter 7) indicate that cover type (e.g., grass, shrub, and bare ground) estimations are profoundly affected by resolution and that percent cover estimations made using one resolution cannot be compared directly with estimations made at another resolution.

  Similarly, models (e.g., NDVI) produced using imagery from one sensor (e.g, Landsat 5 TM) should not be compared directly to models based upon another sensor (e.g., SPOT 5) even when the imagery was collected on the same date. These differences are due to internal differences in the sensors (cf. chapter 10).

- The condition and land cover of arid and semiarid ecosystems --such as those typically considered rangelands-- are greatly influenced by a number of anthropic and environmental factors. The single most influential factor is precipitation (an environmental factor), and, because of this relationship, the use of precipitation as a driver variable in any forecasting model within these regions is critically important to the accuracy of the model. It goes almost without saying then, that the accuracy of the precipitation input layer is also important.

We investigated the use of *in-situ* weather observations, "nearby" weather station observations, and the SOGS weather dataset for use in rangeland condition modeling. The results (cf. chapter 13) suggest the SOGS dataset is required for accurate modeling over any area of interest that is either relatively large or exhibits sufficient relief to disproportionately influence precipitation across a study area.

- Besides precipitation, anthropic factors play a substantial role in determining rangeland condition. In many semiarid ecosystems, cultivated agriculture is not a viable use of the land due to unreliable precipitation patterns. In these areas, livestock grazing is common.

  Livestock grazing in arid and semiarid ecosystems occurs on largely unaltered paddocks. These, in contrast to pasture situations where forage is planted, irrigated, and sometimes mechanically harvested as hay for winter fodder, are left uncultivated by the grazier. The treatment applied to these rangelands is in the form of the livestock itself and the grazier's decision to use *X* number of animals for *Y* number of days.

  The effect grazing animals can have on an ecosystem can be significant and this part of the study focused upon measuring and analyzing soil moisture and land cover response to three treatment types: 1) simulated holistic planned grazing (high stocking rates applied over short time periods), 2) traditional rest-rotation (low stocking rates applied over long time periods followed by periods of partial rest), and 3) total rest (no livestock grazing allowed). The results of this research (cf. chapter 15) are of profound interest and importance: grazing livestock at high stocking rates over short time periods (about 6-7 days) was clearly shown to benefit semiarid rangelands as soil moisture increased by a margin of 10% over the other treatment paddocks used in this study. This suggests that livestock can be better managed using time instead of the quantity of animals.

- Accurately forecasting rangeland condition or predicting changes in semiarid ecosystems is very difficult. This is because the principal driver is precipitation when assuming uniform grazing treatment across the study area. To improve existing modeling software numerous years of land cover data must be allowed as inputs (instead of only two) to better establish trend. In addition, precipitation layers (like the SOGS dataset cf. chapter 13) must be used as site/driver variables. The results of research specifically exploring forecasting models in semiarid ecosystems are given in chapter 16.

- Several hundred people participated in formal public outreach events sponsored by this study (the annual Geospatial Range Sciences Conference and World GIS Day events) and broadened their knowledge of GIS and remote sensing applications to solve real-world problems. Countless other people have benefited from this study, its research results and data sharing as many have visited the study's website, http://giscenter.isu.edu/research/techpg/nasa_oneal/template.htm.

- Two papers have been published in peer reviewed journals and one additional paper is currently in review.

Range Vegetation Assessment of the Upper Snake River Plain, Idaho 2005

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ABSTRACT

Vegetation data was collected at 305 randomly located sample points between June 1 and July 15, 2005 (206 in the USDI BLM Big Desert Region and 99 in the O'Neal Study area located 3 miles north of McCammon, Idaho). We collected data describing percent cover of grasses and shrubs, dominant weed and shrub species, fuel load, sagebrush age, GAP vegetation class, presence of microbial crust, litter type, forage availability, and photo points. Sample points were stratified by fire, grazing, and rest treatments. A high amount of cheatgrass was found as well as a high amount of bare ground. However, in 2005 forage availability increased from previous years, probably due to increased rainfall.

KEYWORDS: vegetation, sampling, GIS, remote sensing, GPS

INTRODUCTION

Many factors influence land cover changes. Wildfire has been, and will always be, a primary source of broad scale land cover change. After a wildfire occurs a change in both plant community composition and plant structure results. In a completely unaltered system, there are plants and shrubs that establish themselves very quickly. In some systems, native plants are in competition with non-native vegetation that is more aggressive. The increase of non-native vegetation can directly result in the reduction of livestock and wildlife carrying capacities. Fire frequency may also increase. An example of non-native vegetation that out competes native vegetation and increases fire frequency is cheatgrass (*Bromus tectorum*). The Big Desert study area is approximately 71 km northwest of Pocatello and the center of the study area is approximately 113º 4' 18.68" W and 43º 14' 27.88" N. (Figure 1)

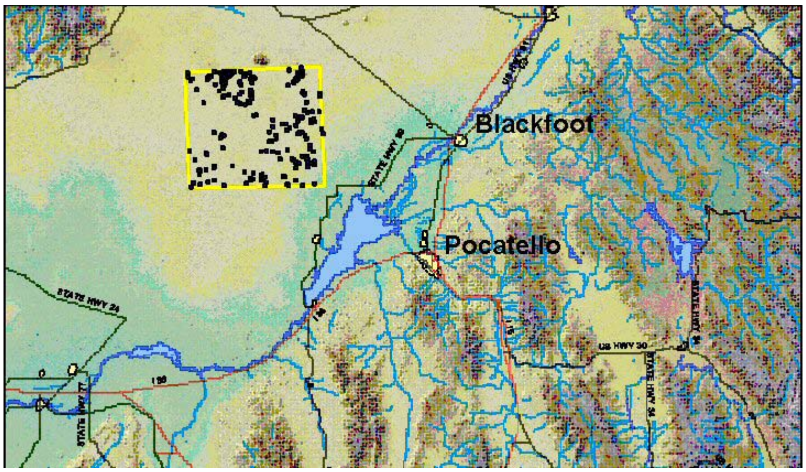

Figure 1. Southeastern Idaho and this study's Area of Concern (bounded in yellow rectangle).

We assessed research in all possible areas; fire, no fire, grazing and no grazing. After comparing various traits in each of these areas we can create generalizations and these generalizations can then shed light on relationships between these variables and may aid range managers in making decisions about prescribed fire and grazing management.

METHODS

Two hundred twenty-five sample points were randomly generated across the study area. Each point met the following criteria;

1) >70 meters from an edge (road, trail, or fence line)
2) <750 meters from a road.

The sample points were stratified by treatment: 1) fire (within the past 10 years) 2) grazing and 3) rest. In 2005 50 points were created in each of these strata. Twenty-five addition points were generated within the boundaries of the 2001 burn area. The location of each point was recorded using a Trimble GeoXT GPS receiver (+/-1m with a 95% CI) using native latitude-longitude (WGS 84)(Serr et al., 2005)Points were occupied until a minimum of 120 positions were acquired and WAAS was used whenever available. All points were post-process differentially corrected using Idaho State University's GPS community base station. The sample points were then projected into Idaho Transverse Mercator NAD 83 using Trimble's Pathfinder office for datum transformation and ESRI's ArcGIS for projection.

Ground Cover Estimation

Visual estimates were made of percent cover for the following; bare ground, litter and duff, grass, shrub, and dominant weed. Cover was classified into one of nine classes (1) None, 2) 1-5%, 3) 6-15%, 4) 16-25%, 5) 26-35%, 6) 36-50%, 7) 51-75%, 8) 76-95%, and 9) >95%).

Observations were assessed by viewing the vegetation while viewing the ground perpendicular to its surfce as technicians walked each site. This was done to emulate what a "satellite sees". In other words the vegetation was viewed from nadir (90 degree angle) as much as possible.

Fuel Load Estimation

Based upon field vegetation training techniques provided by the BLM office in Shoshone Idaho, fuel load was estimated at each sample point. Visual observations of an area equivalent to a Landsat pixel, (28.5mpp or approximately 812 m^2), centered over the sample point were used to estimate fuel load

Table 1. Fuel Load Classes and associated tonnage of fuels.

Fuel Load Classes	(Tons/Acre)
1	0.74
2	1.00
3	2.00
4	4.00
5	>6.00

Note: These categories were derived from Anderson (1982).

Forage Measurement

Available forage was measured using a plastic coated cable hoop 93 inches in circumference, or 0.44 m^2. The hoop was randomly tossed into each of four quadrants (NW, NE, SE, and SW) centered over the sample point. All vegetation within the hoop that was considered adequate forage for cattle, sheep, and wild ungulates was clipped and weighed (+/-1g) using a Pesola scale tared to the weight of an ordinary paper bag. All grass species (except cheatgrass (*Bromus tectorum*)) were considered forage. The measurements were then used to estimate forage amount in AUM's, pounds per acre, and kilograms per hectare (Sheley, Saunders, Henry 1995)

Microbiotic Crust Presence

Microbiotic crusts (Johnston 1997) are formed by living organisms and their by-products, creating a surface crust of soil particles bound together by organic materials. The presence of microbiotic crust was evaluated at each sample point and recorded as either present or absent. Any trace of a microbiotic crust was defined as "presence".

GAP Analysis

Vegetation cover was described using a list of vegetation cover types from the GAP project (Jennings 1997). The GAP vegetation description that most closely described the sample point was selected and recorded.

Litter Type

Litter was defined as any biotic material that is no longer living. Litter decomposes and creates nutrients for new growth. For the litter to decompose it needs to be in contact with the soil in order for the microbes in the soil to break down the dead substance. If the litter is suspended in the air it turns a gray color and takes an immense amount of time to decompose through chemical oxidation. If it is on the ground it is a brownish color and decomposes biologically at a much faster rate. The type of litter present was recorded by color: either gray (oxidizing) or brown litter (decaying).

Big Sagebrush (Artemisia tridentata spp.) Age Estimation

Maximum stem diameter of Big sagebrush plants was measured using calipers (+/-1cm) to approximate the age of each plant (Perryman, Olson 2000) A maximum of four samples were taken at each sample point, one within each quadrant (NW, NE, SE, and SW). The sagebrush plant nearest the plot center within each quadrant was measured using calipers (+/-1cm) and converted to millimeters. The age of each big sagebrush plant was then estimated using the following equation (AGE = 6.1003 + 0.5769 [diameter in mm]).

Photo Points

Digital photos were taken in each of 4 cardinal directions (N, E, S, and W) from the sample point.

RESULTS

Percent Cover Bare Ground, Grass, and Microbiotic Crust

Fifty-six percent of all 2005 field samples (n = 305) had >50% exposed bare ground. The dominant weed --if any were present-- was always cheatgrass. Cheatgrass was present at 71% of points sampled. Thirty percent of the sample points had >5% cheatgrass cover. Eighty-six percent of the samples had <16% grass cover. Microbiotic crust was present at 56 of the 305 points sampled.

Big Sagebrush Age Estimation

The mean age of sagebrush plants was 39.76 yrs (n = 215). The minimum age was 9 yrs and the maximum age was 121 yrs (Figure 2). Twenty-seven sample points fell within the boundary of the 2001 fire. Nineteen of those had no sagebrush plants growing. Of the eight points that had sagebrush present 2 had an average age > 65 and 6 had an average age ≤ 20.

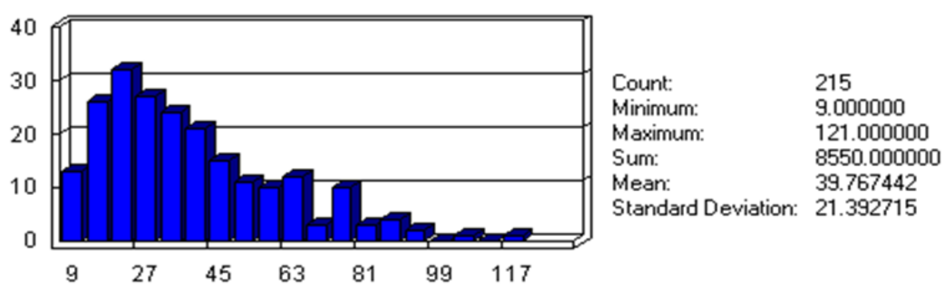

Figure 2. Age distribution of Big Sagebrush in the study area 2005

Forage Measurements

Using AUM Analyzer software (Sheley, Saunders, Henry 1995), forage amount and available Animal Units were calculated for all sample points. Mean forage available was 488.12kg/ha. The minimum forage available was 23 kg/ha and the maximum forage available was 4147 kg/ha.

"Microbial crust is formed by living organisms and their by-products, creating a surface crust of soil particles bound together by organic materials" (Johnston 1997). These are common in very poor rangelands and they are sometimes one of the last things left alive. They can retain water very well even against an osmotic pull. In 2004 only four sample points recorded microbial crust presence, while in 2005 fifty-six of 305 sample points had microbial crust present.

CONCLUSIONS

The available forage present on the range in 2005 varied from what was found in previous years. The calculated pounds per acre and Kilograms per hectare, in sampled areas almost doubled from 2004 to 2005. In 2005 there was a higher amount of precipitation during the month of May than in 2004, which allowed the vegetation to have more moisture available during the peak of the growth cycle (May and early June). Bare ground exposure estimates varied in 2005, appearing to be lower than either of the two previous years. Variations occurred in all five cover types from 2004 to 2005 as illustrated below (figure 3). Variation in percent shrub cover from 2004 to 2005 is probably attributable to the fact that a higher proportion of samples were taken in areas that had burned in the last 10 years in 2005 than in 2004. Recently burned areas (having burned within the last 10 years) are less likely to have developed high shrub cover. Variations in forage, percent bare ground, percent grass, and percent cheat grass may be due to a greater amount of spring moisture during the last two years (Table 2).

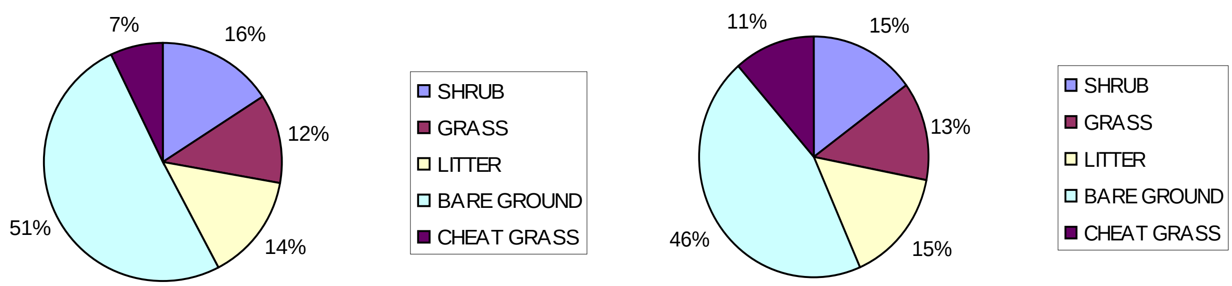

Figure 3.Variations from 2004 (left) and 2005 (right) in the mean percent cover of five cover types observed in the field.

Table 2. Recent annual precipitation (inches)

Month	2003	2004	2005
May	0.53	1.91	2.75
June	0.14	0.56	0.47
July	0.00	1.09	0.14

ACKNOWLEDGEMENTS

This study was made possible by a grant from the National Aeronautics and Space Administration Goddard Space Flight Center (NNG06GD82G). ISU would also like to acknowledge the Idaho Delegation for their assistance in obtaining this grant.

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2006 Range Vegetation Assessment in the Upper Snake River Plain, Idaho

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ABSTRACT

Vegetation data was collected at randomly located sample points between June 5 and September 1, 2006 (n=100 in the USDI BLM Big Desert Region, n=233 in the Hitching Post pasture of the United States Sheep Experiment Station, and n=145 in the ISU O'Neal Ecological Reserve). Data was collected describing the 1) percent cover of grasses and shrubs, 2) dominant weed and shrub species, 3) fuel load, 4) sagebrush age, 5) GAP land cover class, 6) presence of microbial crust, 7) litter type, 8) forage availability, and 9) photo points. Sample points were stratified by fire, grazing, and total rest treatments. The three study areas had variations in the ground cover perhaps due to the different treatments.

KEYWORDS: vegetation, sampling, GIS, remote sensing, GPS

INTRODUCTION

Many factors influence land cover changes. Wildfire has been, and will always be, a primary source of broad scale land cover change. After a wildfire occurs a change in both plant community composition and plant structure results. In a completely unaltered system, there are plants and shrubs that establish themselves very quickly. In some systems, native plants are in competition with non-native vegetation that is more aggressive. The increase of non-native vegetation can directly result in the reduction of livestock and wildlife carrying capacities. Fire frequency may also increase. An example of non-native vegetation that out competes native vegetation and increases fire frequency is cheatgrass (*Bromus tectorum*). The approximate location of the three study areas are shown below (Figure 1).

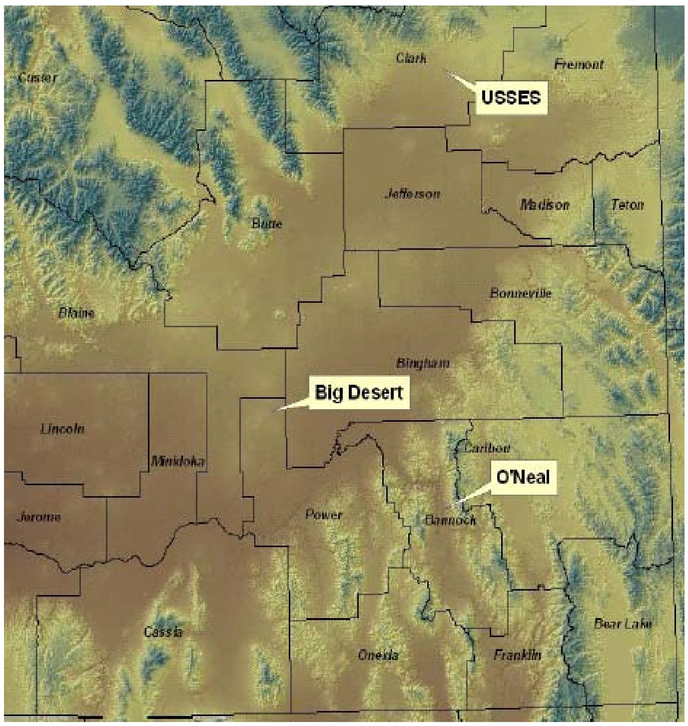

Figure 1. Southeastern Idaho and this study's Area of Concern.

We assessed research in all possible areas; fire, no fire, grazing and no grazing. After comparing various traits in each of these areas we can create generalizations and these generalizations can then shed light on relationships between these variables and may aid range managers in making decisions about prescribed fire and grazing management.

METHODS

Sample points were randomly generated across the study area. Each point met the following criteria;

1) >70 meters from an edge (road, trail, or fence line)
2) <750 meters from a road.

The sample points were stratified by treatment: 1) fire (within the past 10 years) 2) grazing and 3) rest (Table 1). The treatments differed at each study area. The Big Desert covered a much larger geographical location than the other two areas and had a mix of only grazing and fire treatments. The Hitching Post pasture at the USSES had a prescribed burn in September 2005. Most of the points (75%)

there were within the fire boundary. The sample points at the O'Neal Ecological Reserve were evenly distributed among three grazing treatment types: total rest, rest rotation, and high intensity/short duration.

Table 1. Treatment summary for each study area.

	Treatment					
Study Area	**Fire**	**Grazing**	**Fire and Grazing**	**Rest**	**Rest and Fire**	**Sum**
Big Desert	0	51	46	0	3	100
USSES	0	0	0	57	176	233
O'Neal	0	96	0	50	0	146
Sum	0	147	46	107	179	479

The location of each point was recorded using a Trimble GeoXT GPS receiver (+/-0.9 m with a 95% CI) using native latitude-longitude (WGS 84)(Serr et al., 2006)Points were occupied until a minimum of 60 positions were acquired and WAAS was used whenever available. All points were post-process differentially corrected using Idaho State University's GPS community base station. The sample points were then projected into Idaho Transverse Mercator NAD 83 using Trimble's Pathfinder office for datum transformation and ESRI's ArcGIS for projection (Gneiting, et al., 2005).

Ground Cover Estimation

Visual estimates were made of percent cover for the following; bare ground, litter and duff, grass, shrub, and dominant weed. Cover was classified into one of 9 classes (1. None, 2. 1-5%, 3. 6-15%, 4. 16-25%, 5. 26-35%, 6. 36-50%, 7. 51-75%, 8. 76-95%, and 9. >95%).

Observations were assessed by viewing the vegetation perpendicular to the earth's surface as technicians walked each site. This was done to emulate what a "satellite sees". In other words the vegetation was viewed from nadir (90 degree angle) as much as possible.

Fuel Load Estimation

Based upon field vegetation training techniques provided by the BLM office in Shoshone Idaho, fuel load was estimated at each sample point. Visual observations of an area equivalent to a Spot pixel, (10 mpp or approximately 100 m^2), centered over the sample point were used to estimate fuel load (Table 2).

Table 2. Fuel Load Classes and associated tonnage of fuels.

Fuel Load Class	(Tons/Acre)
1	0.74
2	1.00
3	2.00
4	4.00
5	>6.0

Note: These categories were derived from Anderson (1982).

Forage Measurement

Available forage was measured using a plastic coated cable hoop 93 inches in circumference, or 0.44 m^2. The hoop was randomly tossed into each of four quadrants (NW, NE, SE, and SW) centered over the sample point. All vegetation within the hoop that was considered adequate forage for cattle, sheep, and wild ungulates was clipped and weighed (+/-1g) using a Pesola scale tared to the weight of an ordinary paper bag. All grass species were considered forage. The measurements were then used to estimate forage amount in AUM's, pounds per acre, and kilograms per hectare (Sheley et al. 1995). Forage measurements were not made at the USSES.

Microbiotic Crust Presence

Microbiotic crusts (Johnston 1997) are formed by living organisms and their by-products, creating a surface crust of soil particles bound together by organic materials. The presence of microbiotic crust was evaluated at each sample point and recorded as either present or absent. Any trace of a microbiotic crust was defined as “presence”.

GAP Analysis

Land cover was described using a list of vegetation cover types from the GAP project (Jennings 1997). The GAP vegetation description that most closely described the sample point was selected and recorded.

Litter Type

Litter was defined as any biotic material that is no longer living. Litter decomposes and creates nutrients for new growth. For the litter to decompose it needs to be in contact with the soil in order for the microbes in the soil to break down the dead substance. If the litter is suspended in the air it turns a gray color and takes an immense amount of time to decompose through chemical oxidation. If it is on the ground it is a brownish color and decomposes biologically at a much faster rate. The type of litter present was recorded by color: either gray (oxidizing) or brown litter (decaying).

Big Sagebrush (Artemisia tridentata spp.) Age Estimation

Maximum stem diameter of Big sagebrush plants was measured using calipers (+/-1cm) to approximate the age of each plant (Perryman and Olson 2000) A maximum of four samples were taken at each sample point, one within each quadrant (NW, NE, SE, and SW). The sagebrush plant nearest the plot center within each quadrant was measured using calipers (+/-1cm) and converted to millimeters. The age of each big sagebrush plant was then estimated using the following equation (AGE = 6.1003 + 0.5769 [diameter in mm]). Sage measurements were not taken at the USSES.

Photo Points

Digital photos were taken in each of 4 cardinal directions (N, E, S, and W) from the sample point.

RESULTS

Percent Cover Bare Ground, Grass, and Microbiotic Crust

Fifteen percent of all 2006 field samples (n = 479) had >50% exposed bare ground. The dominant weed --if any were present-- was usually cheatgrass. At the USSES the dominant weed was “other” (usually Canada Thistle (Cirsium arvense) at eighty-six percent of the sample points. Cheatgrass was present at

60% of all points sampled. Twenty percent of the sample points had >5% cheatgrass cover. Sixty percent of the samples had <16% grass cover. All the sample points at the O'Neal Reserve had <16% grass cover. Microbiotic crust was present at 184 of the 478 points sampled.

Big Sagebrush Age Estimation

The mean age of sagebrush plants was 24.27 years (n = 181). The minimum age was 10 yrs and the maximum age was 55 yrs (Figure 2).

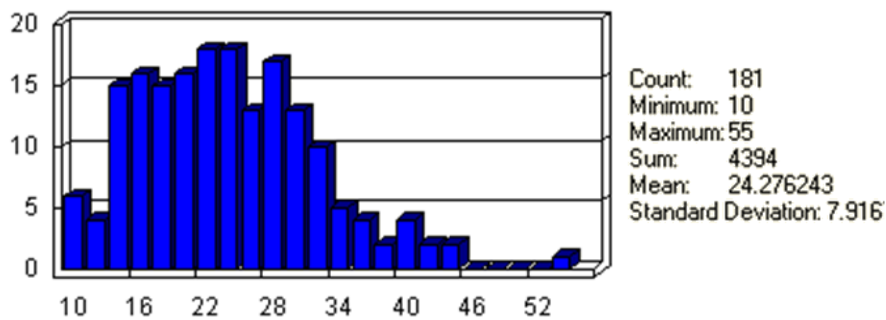

Figure 2. Sagebrush age distribution as sampled during the 2006 field season.

Forage Measurements

Using AUM Analyzer software (Sheley, Saunders, Henry 1995), forage amount and available Animal Units were calculated for the Big Desert and O'Neal sample points. Mean forage available was 226.8 kg/ha. The minimum forage available was 6 kg/ha and the maximum forage available was 1666 kg/ha.

"Microbial crust is formed by living organisms and their by-products, creating a surface crust of soil particles bound together by organic materials" (Johnston 1997). These are common in very poor rangelands and they are sometimes one of the last things left alive. They can retain water very well even against an osmotic pull. In 2005, fifty-six of 305 (18.4%) sample points had microbial crust present, while in 2006 184 of 478 (38.5%)sample points had microbial crust present.

CONCLUSIONS

The differences between the three study areas were interesting. Figures 3-6 are histograms of ground cover estimates for the three study areas and the 2005 data (2005 includes the Big Desert and the O'Neal Reserve). The Big Desert had less bare ground than the other two areas. This area may have benefited from two good rain years, resulting in the lower bare ground. There may have also been some observational bias. The histograms for the USSES and the O'Neal areas match their respective 2005 histograms better than does the Big Desert. These differences may have been caused by different treatments in each of the areas. The Big Desert has a variety of treatments over a large area, the Hitching Post pasture at the USSES burned in 2005 and the O'Neal Study area currently has three different grazing treatments being applied: total rest, rest rotation, and high intensity short duration grazing. The high intensity short duration pasture had very little grass and higher amounts of litter due to the intensity of grazing and little recover time before the vegetation data was collected. O'Neal data was also collected later in the season (August 7, 2006 to September 1, 2006)

One factor affecting ground cover at the USSES was the presence of a large amount of forbs, primarily lupine. Lupine species are known to flourish after a fire. Ninety six of 233 points had forb coverage between 16-25 percent. The fire also affected the grass and shrub cover as there were lower percent shrub and higher percent grass recorded than at the other two study areas. This may be due to the fact that this site is a higher elevation site with a slightly higher moisture regime and a different grazing history.

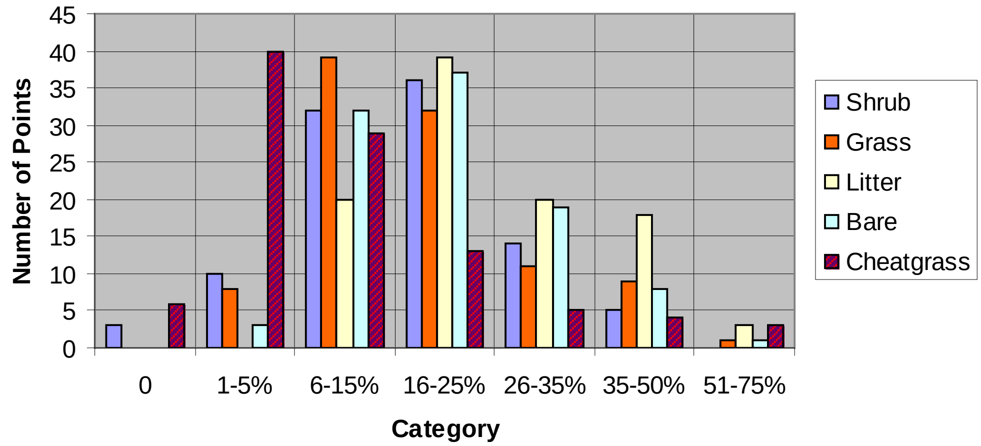

Figure 3. 2006 Big Desert Ground Cover

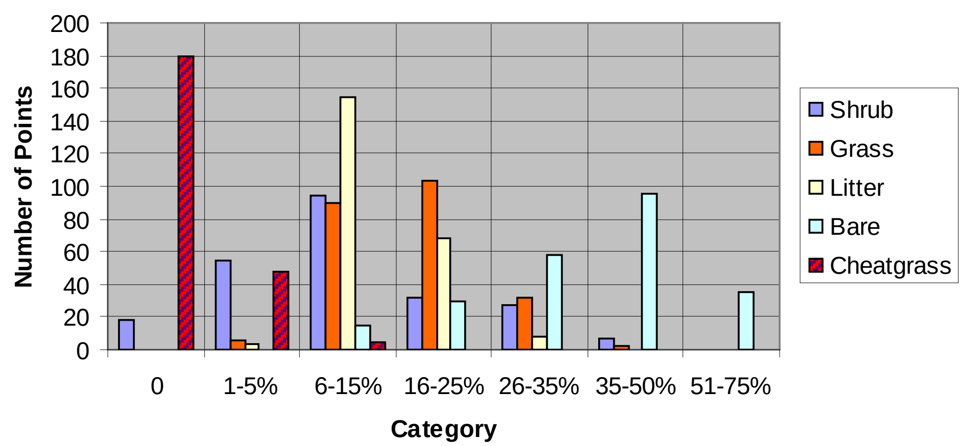

Figure 4. 2006 USSES Ground Cover

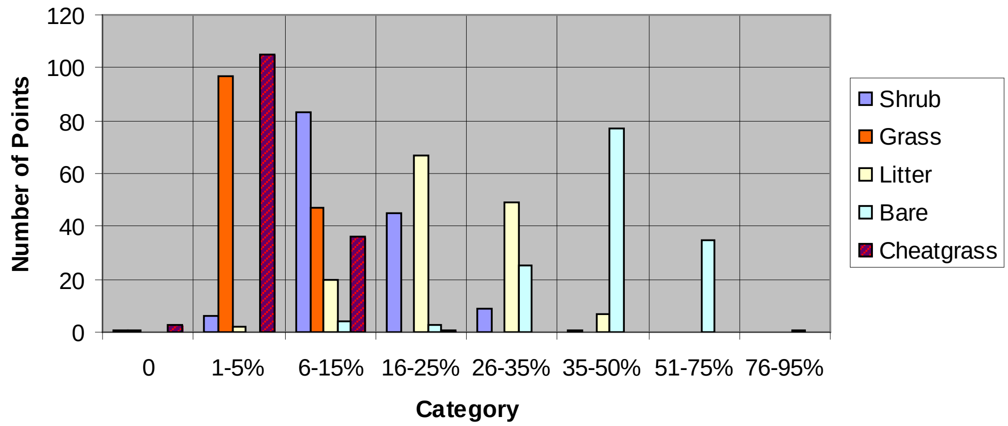

Figure 5. 2006 O'Neal Reserve Ground Cover

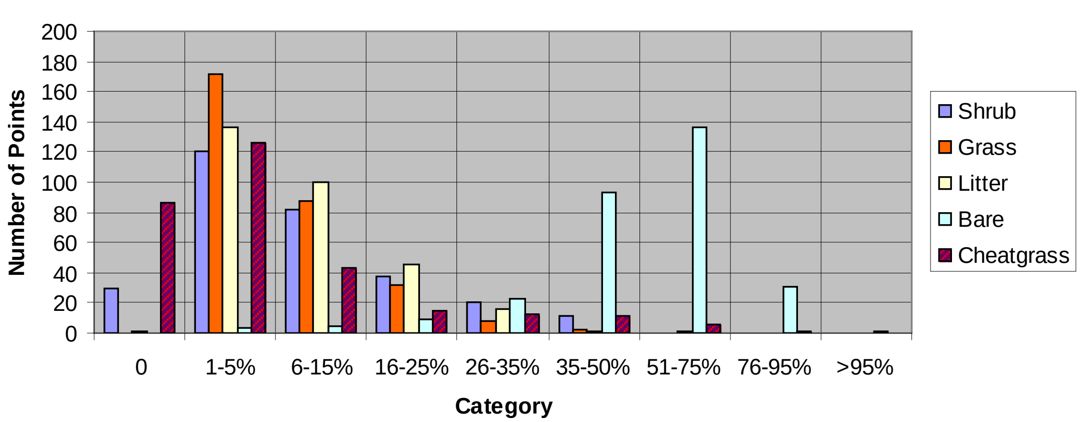

Figure 6. 2005 Ground Cover across all study sites.

ACKNOWLEDGEMENTS

This study was made possible by a grant from the National Aeronautics and Space Administration Goddard Space Flight Center (NNG06GD82G). Idaho State University would also like to acknowledge the Idaho Delegation for their assistance in obtaining this grant.

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2007 Rangeland Vegetation Assessment at the O'Neal Ecological Reserve, Idaho

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ABSTRACT

Vegetation data was collected at stratified, randomly located sample points between June 18 and July 16, 2007 (n=148). Data was collected through both ocular estimation and line-point intercept transects each describing the 1) percent cover of grasses, forbs, shrubs, litter and exposure of bare ground 2) dominant weed and shrub species, 3) fuel load, 4) sagebrush age, 5) GAP land cover class, 6) presence of microbial crust, 7) litter type, 8) forage availability, and 9) photo points. Sample points were stratified by grazing and total rest treatments. The three strata (simulated planned holistic grazing, rest-rotation, and total rest) had variations in the ground cover perhaps due to the different treatments.

KEYWORDS: vegetation, sampling, GIS, remote sensing, GPS, grazing treatment, land management

INTRODUCTION

Many factors influence land cover changes. Wildfire has been, and will always be, a primary source of broad scale land cover change. Also, grazing management decisions and practices has been linked to land cover change. With wildfire or grazing, a change in plant community composition, plant structure, or ecosystem function may result in increases in bare earth exposure and decreases in land sustainability. In some systems, native plants are in competition with non-native vegetation that is more aggressive. The increase of non-native vegetation can directly result in the reduction of livestock and wildlife carrying capacities. Fire frequency may also increase. An example of non-native vegetation that out competes native vegetation and increases fire frequency is cheatgrass (*Bromus tectorum*). A research project located at the O'Neal Ecological Reserve is being conducted to A) determine if planned, SHPG grazing can be used to effectively decrease bare earth exposure B) determine if ground moisture changes relative to bare earth exposure and livestock grazing and C) examine the ecological effects of livestock grazing. The approximate location of the study area is shown below (Figure 1).

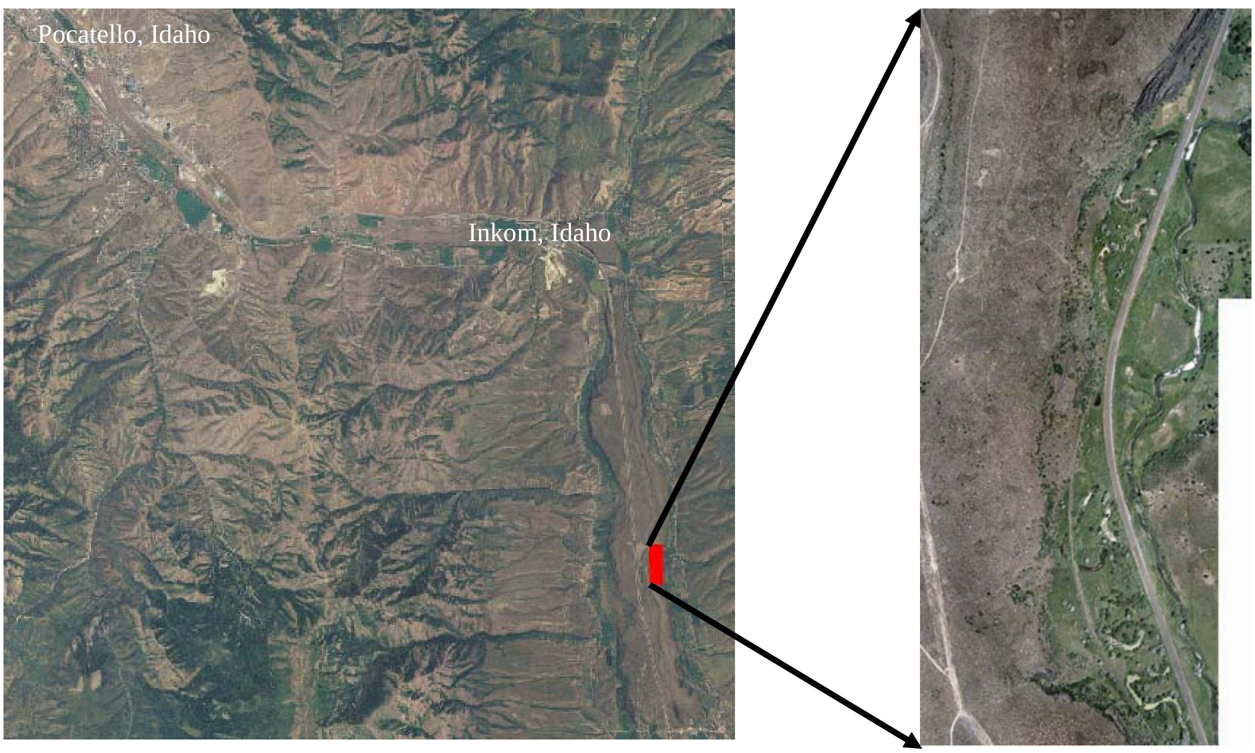

Figure 1. Research study area. The O'Neal Ecological Reserve, represented by red rectangle, is located near McCammon, Idaho.

We sampled three different grazing treatments; adaptive (Simulated Holistic Planned Grazing (SHPG)), rest-rotation (traditional), and total rest (no grazing). After comparing various traits in each of these areas we infer various generalizations which can shed light on relationships between these variables and may aid range managers in making decisions about prescribed and targeted grazing management.

METHODS

Sample points were randomly generated across the study area. Each point met the following criteria:

1) >70 meters from an edge (road, trail, or fence line)
2) <750 meters from a road.

The sample points were stratified by grazing treatment with 50 points in each treatment for a total of 150 sample points. The three grazing treatments were: 1) adaptive (SHPG) 2) rest-rotation and 3) total rest.

The location of each point was recorded using a Trimble GeoXH GPS receiver (+/-0.20 m after post processing with a 95% CI) using latitude-longitude (WGS 84) (Serr et al., 2006). Points were occupied until a minimum of 20 positions were acquired and WAAS was used whenever available. All points were post-process differentially corrected using Idaho State University's GPS community base station. The sample points were then projected into Idaho Transverse Mercator NAD 83 using ESRI's ArcGIS 9.2 for datum transformation and projection (Gneiting, et al., 2005).

Ground Cover Estimation

Estimations were made within 10m x 10m square plots (equivalent to one SPOT 5 satellite image pixel) centered over each sample point with the edges of the plots aligned in cardinal directions. First, visual estimates were made of percent cover for the following; bare ground, litter, grass, shrub, and dominant weed. Cover was classified into one of 9 classes (1. None, 2. 1-5%, 3. 6-15%, 4. 16-25%, 5. 26-35%, 6. 36-50%, 7. 51-75%, 8. 76-95%, and 9. >95%).

Observations were assessed by viewing the vegetation perpendicular to the earth's surface as technicians walked each site. This was done to emulate what a "satellite sees". In other words the vegetation was viewed from nadir (90 degree angle) as much as possible.

Next, transects were used to estimate percent cover of bare ground exposure, rock (>75 mm), litter, herbaceous standing dead, dead standing wood, live herbaceous species, live shrubs, and dominant weed. Percent cover estimates were made along two 10 m line transects. Transects were arranged perpendicular to each other and crossing at the center of the plot at the 5 m mark of each line transect. Using the point-intercept method, observations were recorded every 20 cm along each 10 m line, beginning at 10 cm and ending at 990 cm. The cover type (bare ground exposure, rock (>75 mm), litter, herbaceous standing dead, dead standing wood, live herbaceous species, live shrubs, and dominant weed) at each observation point was recorded (n = 50 points for each line transect and 100 points for each plot).

The litter cover type included biomass that was on the ground and in contact with the ground. Live herbaceous species included live (i.e., green) forbs and grasses, while live shrubs included all species of shrubs.

Fuel Load Estimation

Fuel load was estimated at each sample point. Visual observations of an area equivalent to a SPOT 5 pixel, (10 mpp or approximately 100 m^2), centered over the sample point were used to estimate fuel load. These categories were derived from Anderson (1982) (Table 1).

Table 1. Fuel load classes and associated tonnage of fuels.

Fuel Load Class	Tons/acre
1	0.74
2	1.00
3	2.00
4	4.00
5	>6.0

Forage Measurement

Available forage was measured using a plastic coated cable hoop 2.36 m in circumference, or 0.44 m^2. The hoop was randomly tossed into each of four quadrants (NW, NE, SE, and SW) centered over the sample point. All vegetation within the hoop that was considered forage for cattle, sheep, and wild ungulates was clipped and weighed (+/-1g) using a Pesola scale tared to the weight of an ordinary paper bag. All grass species were considered forage. The measurements were then used to estimate forage amount in AUM's, pounds per acre, and kilograms per hectare (Sheley et al. 1995).

Microbiotic Crust Presence

Microbiotic crusts are formed by living organisms and their by-products, creating a surface crust of ground particles bound together by organic materials. Presence of microbial crust has been linked to degraded rangelands, but is still seen as being better that bare ground as they can retain water very well even against an osmotic pull helping to reduce erosion (Johnston 1997). The presence of microbiotic crust was evaluated at each sample point and recorded as either present or absent. Any trace of a microbiotic crust was defined as "presence".

GAP Analysis

Land cover was described using a list of vegetation cover types from the GAP project (Jennings 1997). The GAP vegetation description that most closely described the sample point was selected and recorded.

Litter Type

Litter was defined as any biotic material that is no longer living. Litter decomposes and creates nutrients for new growth. For the litter to decompose it needs to be in contact with the ground in order for the microbes in the ground to break down the dead substance. If the litter is suspended in the air it turns a gray color and takes an immense amount of time to decompose through chemical oxidation. If it is on the ground it is a brownish color and decomposes biologically at a much faster rate. The type of litter present was recorded by color: either gray (oxidizing) or brown litter (decaying).

Big Sagebrush (Artemisia tridentata spp.) Age Estimation

Maximum stem diameter (up to the first 0.30 m of stem) of Big sagebrush plants was measured using calipers (+/-1cm) to approximate the age of each plant (Perryman and Olson 2000) A maximum of four samples were taken at each sample point, one within each quadrant (NW, NE, SE, and SW). The sagebrush plant nearest the plot center within each quadrant was measured using calipers (+/-1cm) and converted to millimeters. The age of each big sagebrush plant was then estimated using the following equation (AGE = 6.1003 + 0.5769 [diameter in mm]).

Photo Points

Digital photos were taken in each of 4 cardinal directions (N, E, S, and W) from the sample point.

RESULTS

Ground Cover Estimates

Based upon ocular estimates, ten percent of all 2007 field samples (n = 14) had >50 % exposed bare ground and 77 % of samples (n = 113) has bare ground exposure <=35 %. The dominant weed present in 100 % of the 2007 samples was cheatgrass. Eighty-one percent of the sample points had >5% cheatgrass cover where the majority, 82 %, were <= 25 % cover and the maximum cover of cheatgrass was 51-75 % with 1.4 % of samples (n = 2) falling within the maximum range. The majority, sixty-one percent, of the samples had <16 % grass cover.

Based upon transect estimates, the maximum bare ground exposure was 86%, the maximum cheatgrass cover was 53%, the maximum grass cover was 34%, the maximum shrub cover was 66% and the maximum forb cover was 26%.

To truly understand ground cover estimates in relation to grazing treatments, each grazing treatment was independently analyzed. The mean cover classes of each cover type were separated by grazing treatment and are summarized in Table 2.

Table 2. Mean cover class of each cover type separated by grazing treatment.

Cover Class	SHPG Mean Cover	Rest-Rotation Mean Cover	Total-Rest Mean Cover
Bare ground	16-25%	26-35%	16-25%
Shrub	26-35%	36-50%	26-35%
Grass	6-15%	1-5%	6-15%
Litter	26-35%	6-15%	6-15%
Weed	6-15%	16-25%	16-25%
Forb	6-15%	1-5%	1-5%

Ocular estimates were compared with the previous year, 2006. Compared to the 2006 mean cover class, bare-ground exposure has decreased in every grazing treatment. Mean shrub has increased in all but the total-rest treatment. Mean grass, litter, and forb have increased only in the SHPG treatement whereas mean litter decreased in both the rest-rotation and total-rest treatment. Mean weed cover has increased across each treatment.

To qualitativley visualize how the above changes in mean relate to the overall distribution of each cover class, frequency distributions of each cover class were also graphed from 2006 and 2007. The frequency distribution graphs of each grazing treatement from both 2006 and 2007 are shown in figures 2-7.

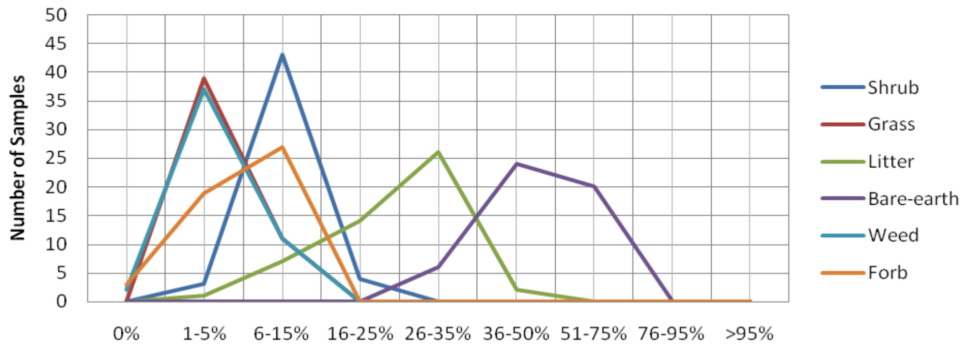

Figure 1. 2006 ground cover estimates in the SHPG grazing treatment. Cover classes are given along the horizontal (x) axis.

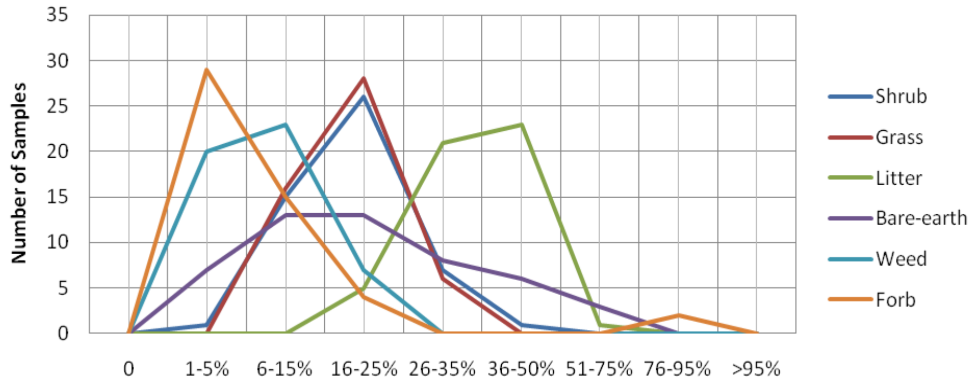

Figure 2. 2007 ground cover estimates in the SHPG grazing treatment. The cover classes are given along the horizontal (x) axis.

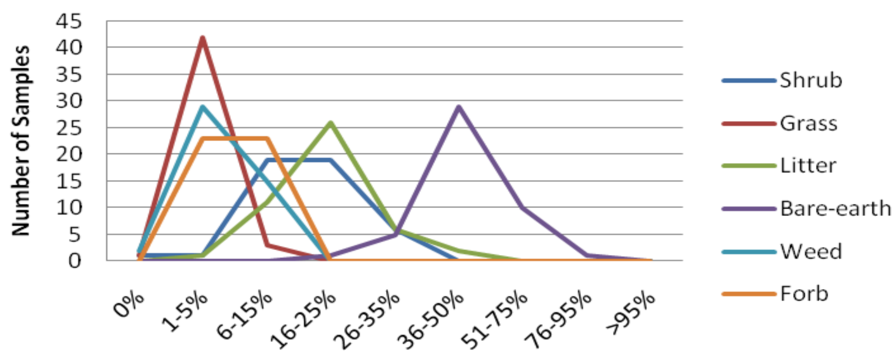

Figure 3. 2006 ground cover estimates in the rest-rotation grazing treatment. The cover classes are along the horizontal (x) axis.

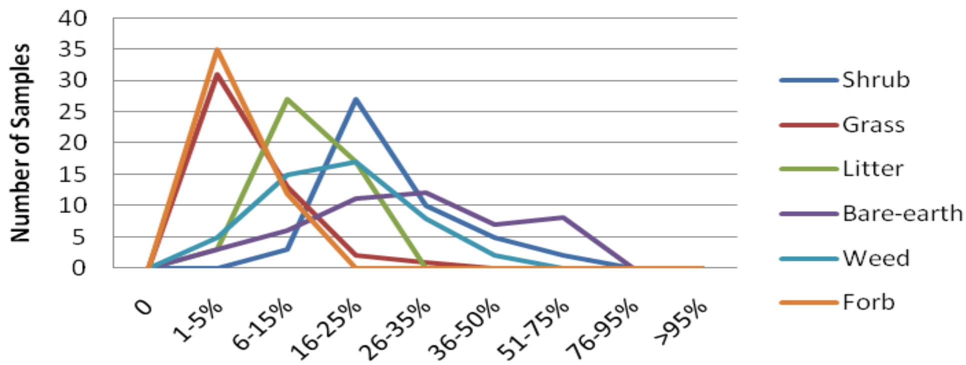

Figure 4. 2007 ground cover estimates in the rest-rotation grazing treatment. The cover classes are given along the horizontal (x) axis.

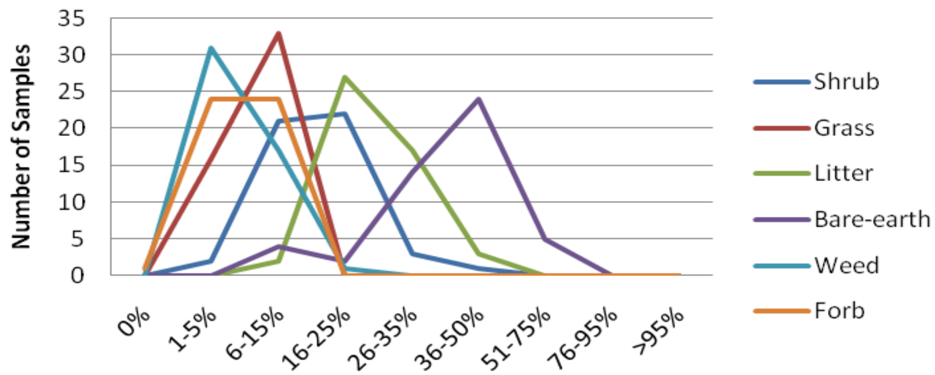

Figure 5. 2006 ground cover estimates in the total rest grazing treatment. The cover classes are given along the horizontal (x) axis.

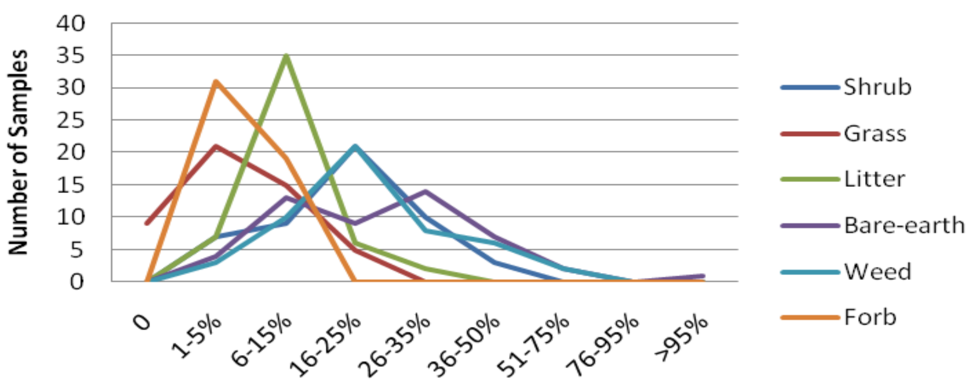

Figure 6. 2007 ground cover estimates in the total rest grazing treatment. The cover classes are given along the horizontal (x) axis.

A two-tailed Mann-Whitney U test was performed to quantify the difference between the distributions of cover classes in 2006 and 2007. The Mann-Whitney test asks if the distribution of a test statistic (ground cover) is the same across two samples. The Mann-Whitney test can be used regardless of distribution normality (mean, median, etc.) and can be used with categorical data (the type of data collected in this study). The results of the Mann-Whitney test are given in Table 3.

Table 3. Summary of two-tailed Mann-Whitney U-test results to determine if cover classes differed within treatment between years (2006 and 2007).

SHPG	**P-Value**
Bare ground	0.000002
Shrub	0.000002
Litter	0.000002
Grass	0.000002
Weed	0.000136
Forb	0.804104 *
Rest-Rotation	
Bare ground	0.000006
Shrub	0.000004
Litter	0.000112
Grass	0.013150
Weed	0.000002
Forb	0.396219 *
Total-Rest	
Bare ground	0.000004
Shrub	0.123248 *
Litter	0.000002
Grass	0.000242
Weed	0.000002
Forb	0.404594 *

Note: cover classes indicated with an asterisk (*) did not differ between years.

Fuel Load Estimation

The majority of field samples (95%; *n*=140) had fuel load estimates between 2-5 tons/acre. The remaining 5 % (*n*=7) had fuel load estimates < 2 tons/acre. The occurrence of fuel loads < 2 tons/acre in 6 of the 7 samples were in areas of high lava rock exposure (>50%) and the remaining 1 sample that was not lava rock had high bare ground exposure >50%.

Forage Measurements

Using AUM Analyzer software (Sheley, Saunders, Henry 1995), forage amount and available Animal Units were calculated. Mean forage available was 77.99 kg/ha with a standard deviation of 61.16. The minimum forage available was 6 kg/ha and the maximum forage available was 287 kg/ha. Grazing treatments were separated to compare available forage between them (Table 4).

Table 4. A comparison of forage estimates across grazing treatments.

Grazing Treatment	Minimum (kg/ha)	Maximum (kg/ha)	Mean (kg/ha)	Standard Deviation
SHPG	23	141	59.53	24.92
Rest-rotation	6	124	39.47	25.72
Total-rest	17	287	132.3	70.80

A statistical test was performed on the forage estimates to check differences between grazing treatment forage estimates. A simple ANOVA was performed which determined that the difference between mean forage estimates between grazing treatments were not statistically different ($p=0.05$). Furthermore, each grazing treatment was individually compared to each other through a paired *t*-test and the differences again were not significantly different. The paired *t*-test results are summarized in Table 5.

Table 5. Results of two-tailed t-test of forage means between grazing treatments. No significant differences were seen (95 % CI).

Hypothesis Tested	Difference Between Means	95% Confidence Interval for Difference Between Means	Two-Tailed P Value
SHPG Mean = Rest-Rotation Mean	20.06	-51.04 to 91.16	0.52
SHPG Mean = Total Rest Mean	-72.77	-221.72 to 76.18	0.33
Rest-Rotation Mean = Total Rest Mean	-92.83	-246.06 to 60.40	0.23

Microbiotic Crust Presence

In 2007, 86.4% of sample points (127 of 147) had microbial crust present. In 2006, 82.1% (119 of 149) had microbial crust. This change in presence of microbial crust is not significant within a 95% confidence interval.

GAP Analysis

Four GAP classifications were observed in 2007—vegetated lava, sagebrush grassland, big sagebrush, and bitterbrush. The majority of sample points (70%; n=103) were classified as sagebrush grassland, 19 % (n=28) as vegetated lava, 9.5% (n=14) as bitterbrush, and 1.4% (n=2) as big sagebrush.

Litter Type

Biologically decaying (brown) litter was dominant at 41% (n=60) of the sample points oxidizing (gray) litter was dominant at 1.4% (n=2) of the sample points while at 57.1% (n=84) of the sample points no discrimination of dominant litter type could be made and the litter type was classified as “both”.

Big Sagebrush Age Estimation

The mean age of sagebrush plants sampled was 18.75 years (*n*= 142). The minimum age was 8 years and the maximum age was 36 years. The standard deviation was 6.63159. Figure 5 shows the frequency distribution of sagebrush age.

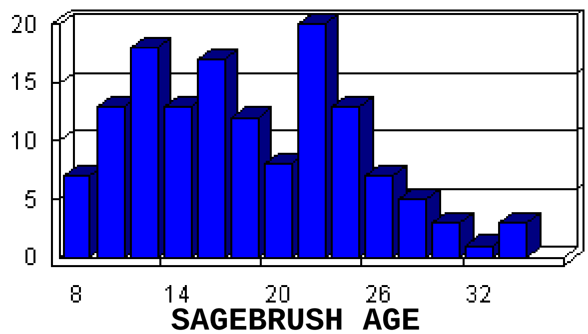

Figure 7. Cumulative frequency graph of sagebrush age estimates at the O'Neal Ecological Reserve.

CONCLUSIONS

The differences between the three treatments were interesting. Figures 2-7 are histograms of ground cover estimates comparison results from 2007 to those from 2006. There were significant differences in cover distributions that could be attributed to differing management practices. Further analysis and comparison with future sampling will hopefully provide better discrimination of these changes.

Desertification and land degradation is primarily evaluated through shifts of the keystone indicator, bare ground exposure. A land manager would want to see smaller percentages of bare ground exposure (i.e. the distribution curve shifts left) while grass, forb, shrub, and litter cover would preferably increase to higher percentages (i.e. the distribution curve shifts right). While differences in bare ground exposure and weed cover distributions (Figures 2-7) were significant in all treatments, it is the direction of the shift that is the major concern. SHPG grazing appears to show the most promise in producing a relatively rapid shift of bare ground exposure toward smaller percentages. These early, albeit non-conclusive, trends can help to re-evaluate management decisions to correct or shift the changes toward more beneficial directions according to management goals and overall sustainability goals

It should be noted that the differences observed were most likely caused by different grazing treatments in each of the areas but observational bias and/or other environmental factors may have contributed to some of these changes. Furthermore, the sampling of the O'Neal was done only 3 weeks after grazing. Some of the changes that are shown, especially in grazed areas, could be different if sampling were done at a different time of year (i.e. pre-grazing or late Fall). However, the purpose of the total rest treatment is to infer the characteristics of the grazed treatments without grazing. But again, analyses of changes in relation to grazing are important in assessing management decisions. The primary goal should be early detection of degradation processes in order to make changes in management before it is too late or desertification thresholds are surpassed.

Regarding shrub cover, there has been an infestation of the sage defoliation moth (*Aroga coloradensis)* at the O'Neal site. In 2006, a large proportion of sagebrush was defoliated and therefore had no photosynthetically active leaves resulting in low sagebrush cover estimats. In 2007, there was a noted increase in recovering sagebrush resulting in higher leaf coverage than 2006. This information may explain the increase in shrub cover in the SHPG and rest-rotation pastures.

ACKNOWLEDGEMENTS

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2008 Rangeland Vegetation Assessment at the O'Neal Ecological Reserve, Idaho

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

ABSTRACT
Vegetation data was collected at stratified, randomly located sample points during May and June, 2008 (*n*=149). Data was collected through both ocular estimation and line-point intercept transects each describing the 1) percent cover of grasses, forbs, shrubs, litter and exposure of bare ground 2) dominant weed and shrub species, 3) fuel load, 4) sagebrush plant age, 5) GAP land cover class, 6) presence of microbial crust, 7) litter type, 8) forage availability, and 9) name of collected photo point files. Sample points were stratified by grazing and rest treatments. The three strata (simulated holistic planned grazing, rest-rotation, and total rest) had variations in the ground cover due to the difference in treatments.

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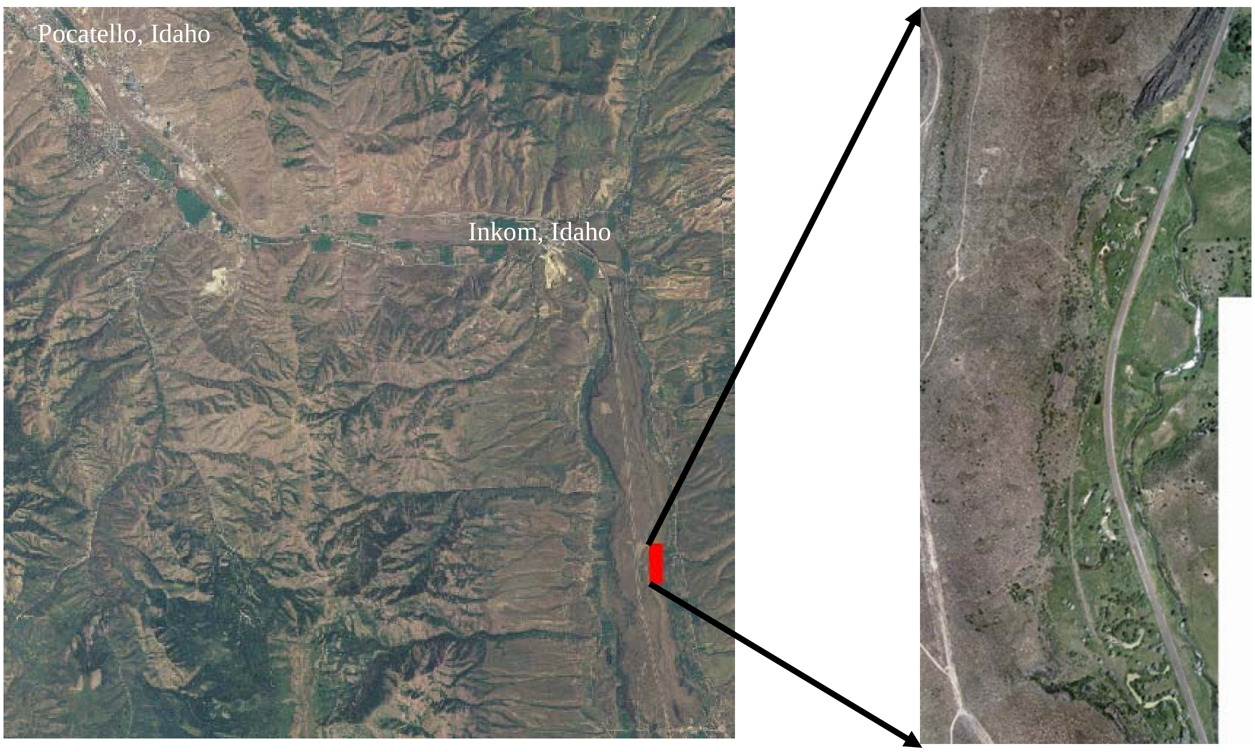

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Sample points were randomly generated across the study area. Each point met the following criteria:

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Fuel load was estimated at each sample point. Visual observations of an area equivalent to a SPOT 5 pixel (10 mpp or approximately 100 m^2) centered over the sample point were used to estimate fuel load. These categories were derived from Anderson (1982) (Table 1).

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5	>6.0

Forage Measurement

Available forage was measured using a plastic coated cable hoop 2.36 m in circumference, or 0.44 m^2. The hoop was randomly tossed into each of four quadrants (NW, NE, SE, and SW) centered over the sample point. All vegetation within the hoop that was considered forage for cattle, sheep, and wild ungulates was clipped and weighed (+/-1g) using a Pesola scale tared to the weight of an ordinary paper bag. All grass species were considered forage. The measurements were then used to estimate forage amount in AUM's, pounds per acre, and kilograms per hectare (Sheley et al. 1995).

Microbiotic Crust Presence

Microbiotic crusts are formed by living organisms and their by-products creating a surface crust of ground particles bound together by organic materials. Presence of microbial crust has been linked to degraded rangelands, but is still seen as being better that bare ground as they can retain water very well even against an osmotic pull helping to reduce erosion (Johnston 1997). The presence of microbiotic crust was evaluated at each sample point and recorded as either present or absent. Any trace of a microbiotic crust was defined as "presence".

GAP Analysis

Land cover was described using a list of vegetation cover types from the GAP project (Jennings 1997). The GAP vegetation description that most closely described the sample point was selected and recorded.

Litter Type

Litter was defined as any biotic material that is no longer living. Litter decomposes and creates nutrients for new growth. For the litter to decompose it needs to be in contact with the ground in order for the microbes in the ground to break down the dead substance. If the litter is suspended in the air it turns a gray color and takes a long period of time to decompose through chemical oxidation. If it is on the ground, litter tends to take on a brownish color and decomposes biologically at a much faster rate. The type of litter present was recorded by color: either gray (oxidizing) or brown litter (decaying).

Big Sagebrush (Artemisia tridentata spp.) Age Estimation

Maximum stem diameter (up to the first 0.30 m of stem) of Big sagebrush plants was measured using calipers (+/-1cm) to approximate the age of each plant (Perryman and Olson 2000) A maximum of four samples were taken at each sample point, one within each quadrant (NW, NE, SE, and SW). The sagebrush plant nearest the plot center within each quadrant was measured using calipers (+/-1cm) and converted to millimeters. The age of each big sagebrush plant was then estimated using the following equation (AGE = 6.1003 + 0.5769 [diameter in mm]).

Photo Points
Digital photos were taken in each of 4 cardinal directions (N, E, S, and W) from the sample point.

RESULTS
Ground Cover Estimates
Based upon ocular estimates, only seven percent of all 2008 field samples (n = 10) had >50 % exposed bare ground and 70% of samples (n = 105) had bare ground exposure <=35 %. The dominant weed present in 100 % of the 2008 samples was cheatgrass. Sixty percent of the sample points had >5% cheatgrass cover where the majority, 98%, were <= 25 % cover and the maximum cover of cheatgrass was 26-35 % with 1.3 % of samples (n = 2) falling within the maximum cover class range.

Based upon transect estimates, the maximum bare ground exposure was 35%, maximum cheatgrass cover was 28%, maximum grass cover was 33%, maximum shrub cover was 59%, and maximum forb cover was 49%.

To truly understand ground cover estimates in relation to grazing treatments, each grazing treatment was independently analyzed. The mean cover classes of each cover type were separated by grazing treatment and are summarized in Table 2.

Table 2. Mean cover class of each cover type separated by grazing treatment.

Cover Class	SHPG Mean Cover Class	Rest-Rotation Mean Cover Class	Total-Rest Mean Cover Class
Bare ground	16-25%	6-15%	1-5%
Shrub	6-15%	6-15%	6-15%
Grass	6-15%	6-15%	6-15%
Litter	16-25%	6-15%	6-15%
Weed	1-5%	6-15%	6-15%
Forb	1-5%	6-15%	1-5%

Ocular estimates were compared with the previous year, 2007. Compared to the 2007 mean cover class, bare-ground exposure has decreased in the Rest-Rotation and the Total-Rest grazing treatments. Both treatment areas seemed to have a rather large decrease as Rest-Rotation moved from a mean cover of 26-35% to 6-15% and Total-Rest moved from 16-25% to 1-5%. Bare ground cover stayed the same in the SHPG area. The mean shrub and weed cover decreased in each treatment. Mean grass only increased in the Rest-Rotation treatement area. There was a decrease in the SHPG area for litter while the other treatment areas remained the same. Forbs decreased in the SHPG area, but had an increase in the Rest-Rotation area, and Total-Rest stayed the same.

To qualitativley visualize how the above changes in mean relate to the overall distribution of each cover class, frequency distributions of each cover class were graphed from 2007 and 2008. The frequency distribution graphs of each grazing treatement from both 2007 and 2008 are shown in figures 2-7.

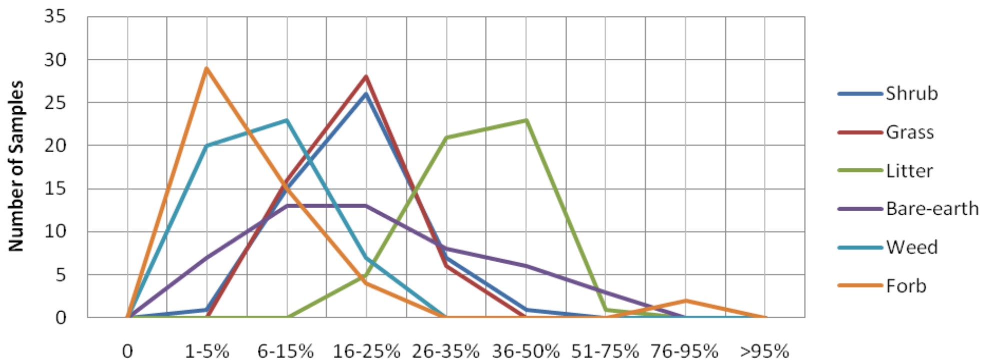

Figure 2. 2007 ground cover estimates in the SHPG grazing treatment. The cover classes are given along the horizontal (x) axis.

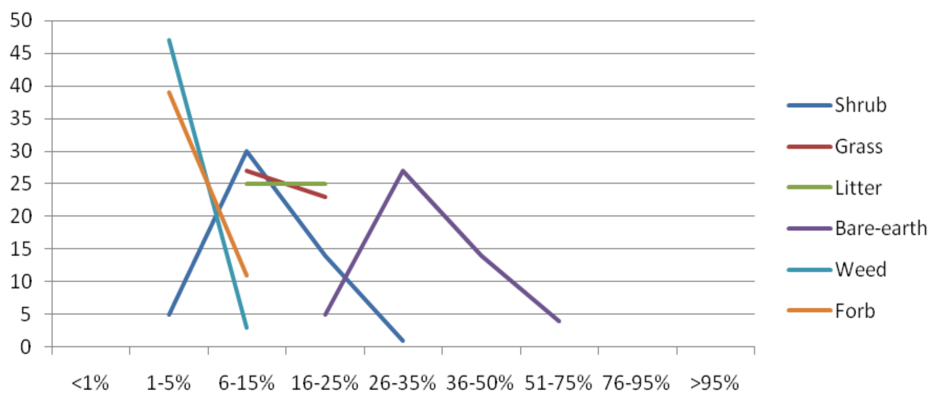

Figure 3. 2008 ground cover estimates in the SHPG grazing treatment. Cover classes are given along the horizontal (x) axis.

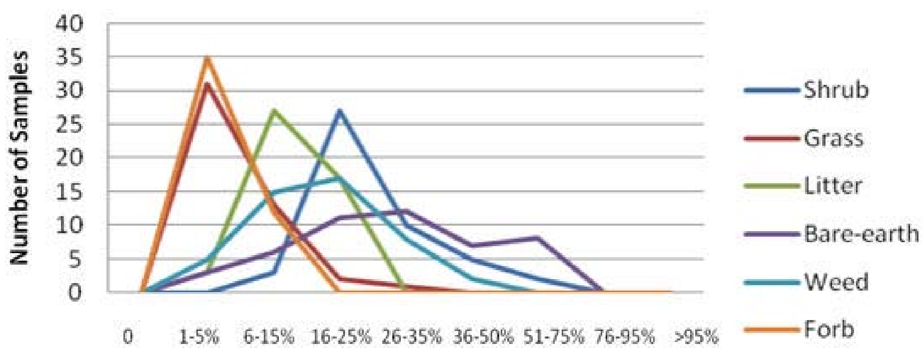

Figure 4. 2007 ground cover estimates in the rest-rotation grazing treatment. The cover classes are given along the horizontal (x) axis.

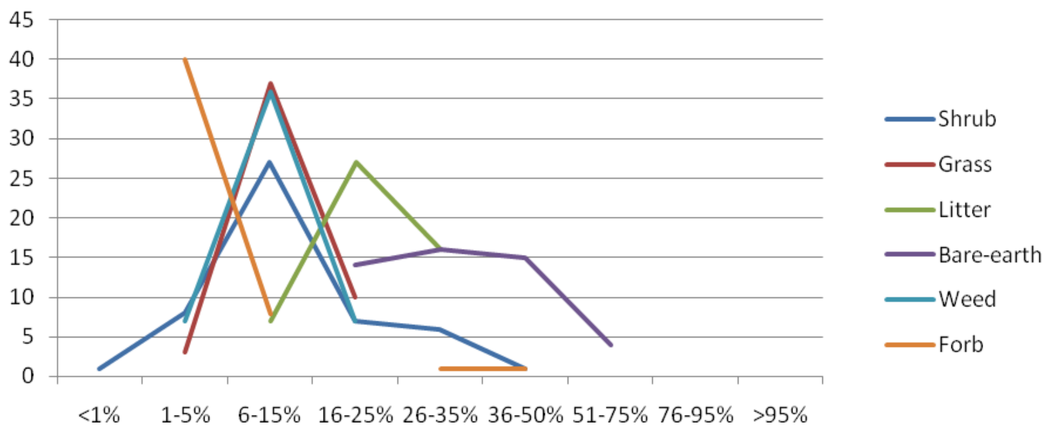

Figure 5. 2008 ground cover estimates in the rest-rotation grazing treatment. The cover classes are along the horizontal (x) axis.

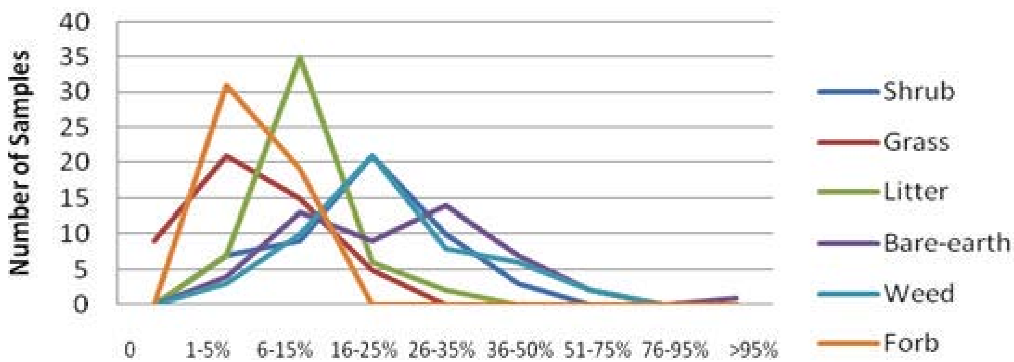

Figure 6. 2007 ground cover estimates in the total rest grazing treatment. The cover classes are given along the horizontal (x) axis.

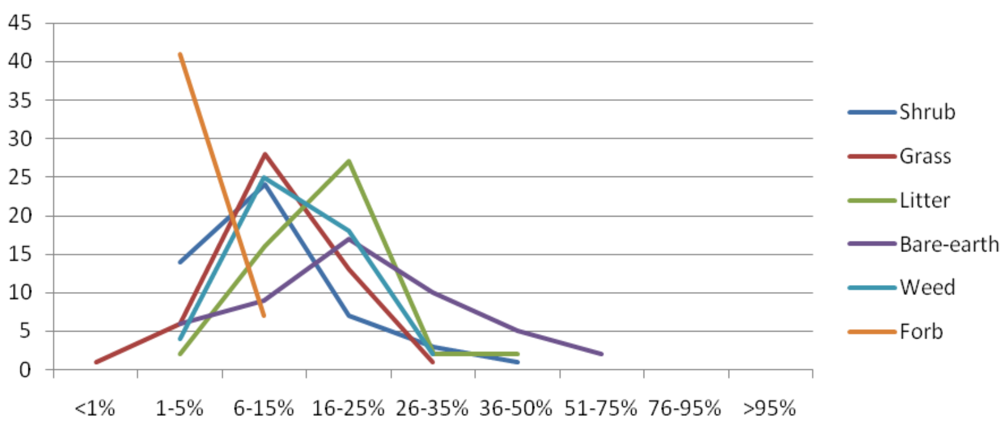

Figure 7. 2008 ground cover estimates in the total rest grazing treatment. The cover classes are given along the horizontal (x) axis.

Statistical Analysis

In order to better understand any differences between vegetation cover within each treatment, the ANOVA test was used. The ANOVA is a simple statistical test which compares varying observations and describes how much the observations differ from the sample mean. The ANOVA test was performed separately for each vegetation class (shrubs, grass, litter, bare ground, weed, and forbs) compared to the same class in the other treatment pastures. The P-Value is the probability value that describes the likelihood the values tested are from the same population and therefore no different from one another. A P-Value of 1.0 would denote no difference while a P-value less than 0.001 would indicate a conservative difference in comparisons. With this in mind, shrubs, grass, and forbs did not have a significant P-value and no difference was assumed among pastures (Table 3). However, litter, bare ground, and weeds all had P-values well below 0.001. F-test results are also shown with F-value and F-critical values given (Table 3) which corroborate significance for these same comparisons. Looking at the F-critical compared to the F-value in Table 3, the difference is not significant for shrubs, grass, and forb classes. However, a difference was found in litter, bare ground, and weeds with the F-Value being much greater than the F-Critical.

Table 3. Results of Anova test between classes (F critical for this test was 3.058)

Class	P-Value	F-Value
Shrubs	0.230	1.483
Grass	0.003	6.111
Litter	$1.11\ E^{-12}$	33.437
Bare Ground	$1.99\ E^{-14}$	39.460
Weed	$7.45\ E^{-12}$	30.695
Forbs	0.087	2.4844

Included in the ANOVA test was a description of the average, or sample mean, between classes in each grazing treatment (SHPG, Rest Rotation, and Total Rest)(Table 4).

Table 4. Summary of Average (sample mean) between classes in each grazing treatments

Class	SHPG	Rest Rotation	Total Rest
Shrubs	11.1	10.8	13.8
Grass	13.8	8.9	12.2
Litter	18.6	12.1	8.4
Bare Ground	17.5	10.3	5.4
Weed	4.5	12.0	12.3
Forb	5.8	6.3	4.1

Fuel Load Estimation

The majority of field samples (87%; n=130) had fuel load estimates of 2 tons/acre. Four percent (n=6) of the field samples had a fuel load of 4 tons/acre which was primarily due to very dense areas of shrub. The remaining 8.7% (n=13) had fuel load estimates < 2 tons/acre. The occurrence of fuel loads < 2 tons/acre in 10 of the 13 samples were in areas of high lava rock exposure; (>50%) 2 of the samples were not in lava rock areas, but had high bare ground exposure with low shrub cover. The last remaining sample was in an area that was disturbed with low gras s and no shrubs.

Forage Measurements

Using AUM Analyzer software (Sheley, Saunders, Henry 1995), forage amount and determined. Mean forage available was 127.44 kg/ha with a standard deviation of 61.16. The minimum forage available was 17 kg/ha and the maximum forage available was 767 kg/ha. Grazing treatments were separated to compare available forage between them (Table 5).

Table 5. A comparison of forage estimates across grazing treatments.

Grazing Treatment	Minimum (kg/ha)	Maximum (kg/ha)	Mean (kg/ha)	Standard Deviation
SHPG	28	186	79.18	24.92
Rest-rotation	17	231	71.86	25.72
Total-rest	34	767	233.41	70.80

Microbiotic Crust Presence

In 2008, 96% of sample points (143 of 149) had microbial crust present. In 2007, 86.4% of sample points (127 of 147) had microbial crust. This change in presence of microbial crust was not significant within a 95% confidence interval.

GAP Analysis

Four GAP classifications were observed in 2008—vegetated lava, sagebrush grassland, bitterbrush, and disturbed. The majority of sample points (61%; *n*=91) were classified as sagebrush grassland, 31.5% (*n*=47) as vegetated lava, 3.4% (*n*=5) as bitterbrush, and 0.6% (*n*=1) as disturbed. Five of the points did not contain data under the GAP classification.

Litter Type

Biologically decaying (brown) litter was dominant at 6.1% (*n*=9) of the sample points while oxidizing (gray) litter was dominant at 4.7% (*n*=7) of the sample points. The remaining 87.9% (*n*=131) of the sample points made no discrimination of dominant litter type and the litter type was classified as “both”. Two of the points did not have any litter data recorded.

Big Sagebrush Age Estimation

The mean age of sagebrush plants sampled was 18.19 years (*n* = 149). The minimum age was 10 years and the maximum age was 47 years. Figure 8 shows a frequency distribution of sagebrush age.

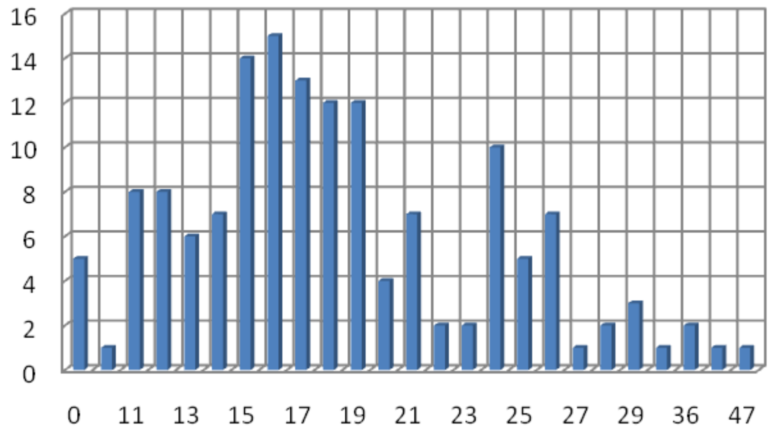

Figure 8. Cumulative frequency graph of sagebrush age estimates at the O'Neal Ecological Reserve, 2008.

CONCLUSIONS

The results from the 2008 field season were interesting when compared with the results from 2007. Figures 2-7 give a visual representation of changes between 2007 and 2008 for each vegetation class separated by treatment pasture. These graphs show a tendency towards a decrease in most cover classes. Weed and shrubs both saw a decrease in all grazing treatments with an increase of grass and forbs seen in the Rest-Rotation treatment area.

The mean forage estimates compared to 2007 saw a general increase especially in the Total Rest pasture. The mean increased from 132.3 kg/ha in 2007 to 233.41 kg/ha in 2008. In the Rest-Rotation pasture the mean increased from 39.47 kg/ha to 71.86 kg/ha in 2008 while the SHPG pasture had similar results increasing from 59.53 kg/ha in 2007 to 79.18 in 2008. The differences observed could be due to effective grazing treatments, but observational bias as well as environmental factors should be noted as possible influences to changes from the previous year. During the sampling process at the O'Neal rain fell consistently throughout the time spent on site. If the grass clippings had absorbed a lot of rain water at the time of weighing, the final weight would have been altered especially if the samples were not thoroughly dried prior to weighing. This factor may be the reason for the large increase in average forage weight from 2007 to 2008. Again, further comparison and sampling will better analyze this trend, and help to conclude if the grazing treatments are effective.

It is important for a land manager to see smaller percentages in bare ground exposure. The Rest-Rotation treatment area as well as the Total Rest area both saw a decrease in bare ground exposure while the Simulated Holistic Planned Grazing allotment kept the same average percent range from 2007 to 2008. Looking at the results from the 2007 study shows there was a decrease in the SHPG treatment from 2006 in overall bare ground exposure. This means the SHPG allotment is moving towards decreased bare ground exposure. On average the percentage remained the same, and it is important to note there was not an increase. If the study were to continue, it would be interesting to learn if these trends will continue towards a decrease in bare ground exposure.

ACKNOWLEDGEMENTS
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2009 Rangeland Vegetation Assessment at the O'Neal Ecological Reserve, Idaho

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ABSTRACT
Vegetation data were collected at 30 randomly located sample points during June 2009. Data were collected using both ocular estimation and line-point intercept transects each describing fuel load and percent cover of grasses, forbs, shrubs, litter, microbial crust, bare ground, and weeds respectively. In the SHPG (Simulated Holistic Planned Grazing) grazing treatment of the O'Neal, percent cover of grass (2009=24.66%, 2008=13.84%), forbs (7%, 5.82%), and shrubs (12.33%, 11.1%) increased from 2008. The Rest-Rotation grazing allotment also saw increased percentage cover in grasses (22.66%, 8.96%), forbs (9.16%, 6.34%) and shrubs (13.83%, 11.26%). In the Total Rest grazing allotment, percent cover increased in grasses (28.33%, 12.27%), forbs (10.33%, 4.1%), and weeds (13.6%, 12.33%). Much of the changes observed are likely attributable to the increase in precipitation in 2009 (106.8 mm) relative to 2008 (9.2 mm).

KEYWORDS: Vegetation, sampling, GIS, remote sensing, GPS, grazing treatment, land management

INTRODUCTION

There are many factors that influence land cover changes. Wildfire has been, and will always be, a primary source of broad scale land cover change. In addition, grazing management decisions and practices have also been linked to land cover change. With wildfire or grazing, a change in plant community composition, plant structure, or ecosystem function may result in increases in bare ground and decreases in land productivity. The introduction of non-native vegetation can lead to a degraded system due to the competition placed upon native plant life and the change in plant community composition. An increase in non-native vegetation may reduce the rangeland's ability to support livestock and wildlife, and may reduce its resiliency to larger, catastrophic events. Cheatgrass (*Bromus tectorum*) is an example of a non-native species that has greatly affected rangeland ecosystems throughout the Intermountain West.

This paper describes the vegetation/land cover sampling performed during the summer of 2009 which was performed to support on-going rangeland research at Idaho State University's GIS Training and Research Center (Anderson et al, 2008; Gregory et al., 2008; Russell and Weber, 2003; Sander and Weber, 2004; Tedrow, Davis, and Weber, 2008; Underwood et al, 2008; Weber and McMahan, 2005). In this study, land cover was estimated using line-point intercept transects and these data were used to foster a better understanding of the effect of grazing management practices at the O'Neal Ecological Reserve, with potential application to other semiarid rangelands around the world.

METHODS

Study Area

Research at the O'Neal Ecological Reserve is being conducted to A) determine if Simulated Holistic Planned Grazing can be used to effectively decrease bare ground exposure, B) determine if soil moisture changes relative to bare ground exposure and treatment, and C) examine the ecological effects of livestock grazing. The approximate location of the study area is shown below (Figure 1).

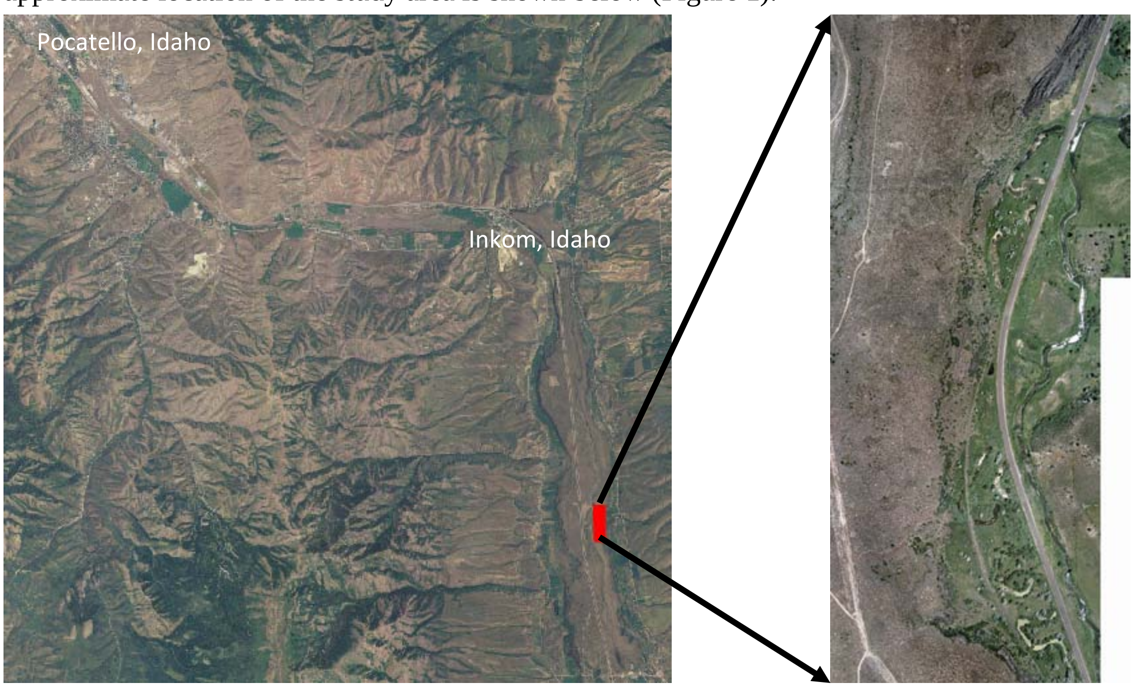

Figure 1. Research study area. The O'Neal Ecological Reserve, represented by red rectangle, is located near McCammon, Idaho.

Three different grazing treatments were sampled; Simulated Planned Holistic Grazing (SHPG), rest-rotation (RESTROT), and total rest (TREST). After comparing several metrics for each of these areas we infer various generalizations which may shed light on relationships between the measured variables and aid range managers in making decisions about prescribed and targeted grazing management.

Field data collection

Sample points for this study were randomly generated based on criteria determined prior to collecting the data. These criteria include: all points must be 1) >70 meters from an edge (road, trail, or fence line) and 2) <750 meters from a road. There were 30 points generated in total throughout the three O'Neal grazing pastures. The three grazing treatments were: 1) Simulated Holistic Planned Grazing (SHPG) 2) rest-rotation (RESTROT) and 3) total rest (TREST). A new criterion considered for the 2009 study included placing an east or west bearing on each sample point depending on its location in reference to the flight line of a concurrently acquired high-resolution (0.05mpp) aerial photography mission. If the random sample point was located to the west of the flight line path, then the point would be marked with an E to indicate the transect would be read to the east of the sample point (plot center), in contrast, if the random sample point was located to the east of the flight line path, then the transect would read directly to the west of plot center. This was done to ensure the entire transect would be acquired by the aerial photography mission.

Sample points were navigated to using a Trimble GeoXH GPS receiver. A 20 m flexible tape was laid out on the ground from the starting point (plot center) and in the designated direction (directly east or west) with the aid of a compass. Photographs were taken using a Sony digital camera in each cardinal direction, starting at north and proceeding to photographs viewing east, south, and west. Land cover type was determined by looking straight down at the transect tape and recording the land cover feature in the upper most canopy directly above the designated observation point. Observation points began at 10 cm from the sample point (observation point one) and continued every 20 cm thereafter (observation points 2-100). Land cover at each observation point was classified as either shrub, rock (if the rock was over 7.5 cm in surface diameter), bare soil, invasive weed, grass, forb, litter, standing dead herbaceous material, standing dead woody material (e.g., a dead tree or sagebrush shrub still intact at the ground), or microbiotic crust. A total of 100 point observations were made and recorded in the GPS-based field form.

The Trimble GeoXH GPS receiver (+/-0.20 m @ 95% CI after post processing) using latitude-longitude (WGS 84) was used to record the location of each sample point (Serr et al., 2006). Points were occupied until a minimum of 60 points were acquired and WAAS was used whenever available. All points were post-process differentially corrected using a constellation of GPS base stations each located <80km from the study area. This technique used Trimble's H-star technology to achieve improved horizontal positional accuracy. The sample points were projected into Idaho Transverse Mercator NAD 83 using ESRI's ArcGIS 9.3.1 for datum transformation and projection (Gneiting, et al., 2005).

Fuel load was determined by visually estimating the vegetation type and quantity in the immediate vicinity (approximately 20 meters) of the sample point. Anderson's (1982) fuel load classes were used (Table 1).

Table 1. Fuel load classes used in this study

Fuel Load Class	(Tons/Acre)	Description
1	0.74	Almost bare ground, very little vegetation
2	1.00	Grasses, some bare ground, few shrubs
3	2.00	Mixture of shrubs and grasses
4	4.00	Predominantly shrubs
5	>6.00	Shrubs to trees

RESULTS

Based upon land cover estimates, maximum bare ground was 26%, maximum weed cover was 25%, maximum grass cover was 46%, maximum shrub cover was 33%, and maximum forb cover was 24%.

Each grazing treatment was independently analyzed in order to better understand how land cover responded in relation to each grazing treatments. The mean cover of each cover type were separated by grazing treatment and summarized in Table 2.

Table 2. Mean cover of each land cover type by grazing treatment (2009).

	Mean cover (%)		
Land cover class	SHPG (*n*=3)	Rest-rotation (*n*=24)	Total rest (*n*=3)
Bare Ground	15.33	8.12	2.00
Shrub	12.33	13.83	13.00
Grass	24.66	22.66	28.33
Litter	9.33	9.04	7.60
Weed	3.00	8.25	13.60
Forb	7.00	9.16	10.33

Compared to a similar sampling campaign during the summer of 2008 (n = 150), 2009 showed a decrease in bare ground and litter across all treatment pastures as well as a decrease in weed cover in both the SHPG and rest-rotation pastures. In contrast, there was an increase in grass and forb cover found across all treatment pastures which is most probably the result of increased precipitation in 2009 relative to that in 2008. In June of 2008 the total rainfall was 9.2 mm with the monthly average at 0.025 mm. This differs greatly from June 2009 which had a total rainfall of 106.8 mm and a daily average of 0.296 mm. Similarly, there was an increase in shrub cover in both the SHPG and rest-rotation pastures as well as an increase in weed cover in the total rest pasture. The latter change may be due to the absence of grazing which in turn may favor the establishment of invasive annual weeds such as cheatgrass (Table 3). It is noted however, that these changes are observations based upon absolute values and not the result of a statistical comparison of inter-annual differences within each pasture. Statistical analyses were not performed as the number of samples was not sufficient.

Table 3. Mean cover of each land cover type by grazing treatment (2008).

	Mean cover (%)		
Land cover class	SHPG (*n*=50)	Rest-rotation (*n*=50)	Total rest (*n*=50)
Bare Ground	17.52	10.36	5.47
Shrub	11.1	11.26	13.86
Grass	13.84	8.96	12.27
Litter	18.68	12.14	8.47
Weed	4.5	12.04	12.33
Forb	5.82	6.34	4.10

In 2009, the SHPG was not grazed, which may be a factor explaining the increased grasses and forbs compared to the summer of 2008 when the allotment had been grazed. The RESTROT pasture was grazed in 2009 and 2008, and in this case an increase similar to that found in the SHPG treatment area was observed. This suggests the changes observed in the SHPG pasture is attributable more to the increase in precipitation (environmental effects) than grazing (anthropic effects). The small number of samples in both the SHPG (*n*=3) and TREST (*n*=3) pastures in 2009 compared with the number of samples taken from the RESTROT (*n*=24) pasture could also be a factor affecting the reported results.

CONCLUSIONS

The results from 2009 field season saw some dramatic changes when compared with the results from 2008. There was an increase in both grass and forb cover classes across all three grazing treatments (Tables 2 and 3). In addition, there was also a decrease in bare ground and litter in each pasture.

Higher percentages of grass cover are very important to provide a healthy environment for both livestock and wildlife and in 2009 there was a substantial increase in grass cover. Each allotment increased from 2008 by an average of 13.5%. The differences observed could be due to more effective grazing treatments, but observational bias as well as environmental factors should be noted as possible influences to changes reported from the previous year. During June of 2009, rain fell consistently at the O'Neal site, resulting in an increase in precipitation from 2008 by 97.6 mm. This is most probably the principle factor in the increased growth of grasses and forbs. However, further comparisons would help to better analyze whether there were any grazing treatments effects as well.

Bare ground decreased by an average of 2.63% while litter decreased by an average of 4.44%. Comparing the 2008 results with the summer of 2007 shows a similar trend of decreasing bare ground and litter. The RESTROT pasture and TREST pasture both exhibited a decrease in bare ground while the SHPG allotment maintained the same average percent bare ground from 2007 to 2008. It should be noted, however, that not as many sample points were taken within the SHPG pasture (*n*=3) and TREST pasture (*n*=3) as compared with the sample size from the RESTROT pasture (*n*=24). This could be a factor affecting the reported results, but the general trend towards a decrease in bare ground suggests an overall improvement. Further sampling and monitoring will more definitively indicate if these trends will continue towards a reduction in bare ground.

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Accurate Mapping of Ground Control Points for Image Rectification and Holistic Planned Grazing Preparation

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ABSTRACT

Managing livestock grazing for improving or maintaining rangeland condition is controversial and difficult. It has been suggested that holistic planned grazing will not only maintain rangeland condition, but improve it. A study will be conducted by Idaho State University's GIS Center to test this hypothesis. In order to prepare a study area for this experiment some initial ground work was needed. Five centimeter resolution aerial imagery was to be taken of the entire study area to provide visual documentation of the condition of the study area prior to onset of the experiment. Before the imagery was flown Ground Control Points were established and mapped to +/- 2 cm accuracy using survey grade GPS. Fences that split the study area into two separate pastures were mapped using GIS and marked in the field using GPS for navigation. Pre-study ground truth data was taken at 100 different locations throughout the study area. At the conclusion of this project, the study area was ready for the holistic planned grazing experiment.

KEYWORDS: Planned grazing, GIS, Ground control points

INTRODUCTION

Range management is the manipulation of rangelands to produce goods and services for society. There are two basic components of range management. They are "(1) protection and enhancement of the soil and vegetation complex, and (2) maintaining or improving the output of consumable range products, such as red meat, fiber, wood, water, and wildlife" (Holecheck et al., 2001). Managing livestock grazing for improving or maintaining rangeland condition is controversial and difficult. There are differing theories as to what biological processes are affected by grazing and which grazing systems have the least affect on these processes (Walker, 1995).

One grazing technique that has been suggested to recoup natural vegetation is holistic planned grazing (Savory and Butterfield, 1999). This method for managing rangelands requires high intensity grazing for short durations. The high intensity grazing breaks up crusted soil and standing senesced vegetation through trampling. The trampled vegetation becomes litter which covers the bare land. Litter conserves soil moisture by reducing evaporation, protects soil from heat and adds nutrients to soil through decay (Williams et al., 1993). The protected soil is then more suitable for growing new vegetation.

A study implementing planned grazing will be conducted by ISU's GIS Training and Research center to test the effectiveness of planned grazing in restoring natural vegetation. Before implementing the planned grazing study some preparation work needed to be performed.

The purpose of this project was to prepare an area for a holistic planned grazing study where the effects of the grazing could be monitored and analyzed using geotechnologies. Pre-study five centimeter resolution aerial imagery was taken to establish visual documentation of the condition of the land prior to the study. To accomplish the purpose of the project and to ensure accurate georectification of the imagery ground control points (GCP)s had to be established and their exact spatial location recorded; fences needed to be planned, mapped, and erected within the study area and initial ground truth data had to be collected. The preparation work was completed during the summer months (July and August) of 2005.

METHODS

Aerial imagery was flown over the entire study area. Ten GCPs were setup strategically throughout the flight path in a pattern recommended by the vendor, 3Di Corporation. The location of the GCPs and the boundary of the O'Neal study area are shown below (figure 1). The GCPs were setup using two strips of reinforced plastic, six inches wide and six feet long, laid across each other in the shape of a cross (+). All GCPs were oriented with each arm of the cross pointing in one of the four cardinal directions (north, south, east, west). Each GCP was covered with chicken wire and staked down with eight inch spikes to ensure it would remain in place. After placement of each GCP a GPS location was recorded at the center of the cross using a Trimble GeoXT GPS unit.

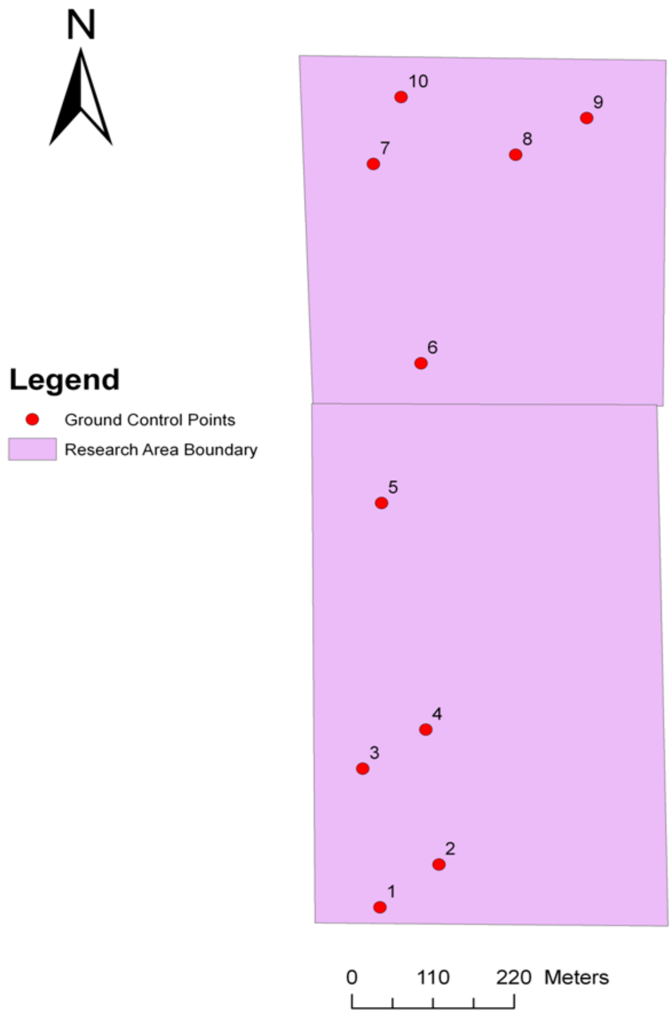

Figure 1. O'Neal study area ground control point locations

The Trimble GeoXT GPS receiver is capable of (+/-0.7m with a 95% CI) using native latitude-longitude (WGS 84)(Serr et al., 2005). In order to georeference an image with five centimeter resolution, GCP's with +/- 3.4 cm accuracy was required. To collect GCP locations to satisfy this requirement, survey grade GPS units were needed. The units chosen for this were Leica SR530 units capable of (+/- 0.1m @ 95% CI) (Serr et al., 2005). Two units were needed; one to be used as a base station and one to be used as a rover. Note: the total station was required as real-time correction signals were not available in the somewhat remote study area.

The Base station occupied a previously surveyed BLM survey monument (Township 8, Range 36 E NW 1/16 section 26 E, year 2002), so future work could be executed using location information collected from this project. The base station was started and allowed to collect static observations (positions) for at least two hours. Multiple positions were recorded so averaging could be performed to obtain the precise location of the base station.

Using the Trimble GeoXT unit each of the previously installed ground control points was located from records taken at the time of installation. The Leica SR530 rover GPS unit was connected to a two meter tall antenna. The base of the antenna was set in the center of each GCP using the spike or re-bar as the reference. The rover collected locational information from satellites and from the base station. At least 40 positions were recorded at each GCP location so they could be averaged for an accurate (+/- 3.4 cm) determination of the center of the GCP.

Location data collected by the base station and rover was downloaded in the lab by technicians using Leica Ski_Pro software. Each Leica SR530 was connected to the desktop computer in the lab and data was transferred from the storage card in the unit to the hard drive of the desktop. The positions were then viewed as points on a map and as a table with their coordinates and other information listed.

The downloaded raw data was sent to the Online Positioning User Service (OPUS) to be corrected based on the positions recorded by the base station, the known location of the survey marker and three Continuously Operating Reference Stations (CORS) sites (http://www.ngs.noaa.gov/OPUS/What_is_OPUS.html). The corrected data was accurate to +/- 2 cm which was better than the 3.4 cm accuracy required. These data were used for georeferencing the aerial imagery by 3Di Corporation.

Fencing of the study area to ensure that only holistic planned grazing would take place was the next step. Fence lines were drawn inside the boundary of the property using ArcGIS software. The study area was split into two pastures, one to be grazed holistically (north pasture) and one to be rested (south pasture). The fence lines were flagged every 50 feet within the study area by using a Trimble GeoXT for navigation. The fencing was then completed by an independent contractor, Pro-tech fence of Blackfoot, Idaho.

One-hundred sample points were randomly generated across the study area; twenty five points were generated within the south pasture; fifty points were generated within the north pasture; and 25 points were generated outside the pastures within a BLM grazing allotment that implements traditional rest-rotation grazing. Each point met the following criteria; 1) >70 meters from an edge (road, trail, or fence line) 2) <750 meters from a road. Ground truth data was collected according to methodology used by ISU's GIS TReC (Sander and Weber, 2004).

RESULTS

Upon completion of this project the aerial imagery (figure 2) was successfully co-registered and delivered. Pre-grazing ground truth data is available, and the study area is fenced, ready for grazers.

Figure 2. Aerial imagery of the O'Neal study area

DISCUSSION

Establishing easily visible GCPs whose location information is accurate to +/- 2 cm allows for very accurate georeferencing of the five centimeter resolution aerial imagery. The accurate imagery can now be used to create a vegetation census of the O'Neal study area. The high resolution imagery will also provide a good visual documentation of the condition of the land prior to the planned grazing study and can serve as a reference in future years.

The next step of the project is to erect GCPs that can be detected within the 2.4 m resolution of Quickbird satellite imagery. A very accurate rangeland health model has been created using Quickbird imagery. One problem with this imagery, however, is that exact co-registration of Quickbird imagery with patchy targets (e.g., new weed infestations) was difficult due to its high spatial resolution. Highly visible, large ground control points (GCP) would enable the imagery to be accurately georeferenced and co-registered with field observations located using GPS. Accurate georeferencing will result in a more accurate model which will result in more conclusive evidence of changes within the O'Neal study area due to planned grazing.

The GCPs erected for the Quickbird imagery will need to be much larger than the ones created for the aerial imagery. The techniques used for establishing the accurate location of the GCPs this year, however, can be used for mapping the new GCPs that will be erected in the future.

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Effect of Spatial Resolution on Cover Estimates of Rangeland Vegetation in Southeastern Idaho

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ABSTRACT

High-resolution aerial imagery has been frequently used to study rangelands. Still, due to resolution limitations, it is not always possible to identify plant species or ground cover accurately. The objective of this study was to use high resolution aerial imagery (1.0 m, 0.3m and 0.15m spatial resolution) to: 1) determine the percent cover of shrubs and grasses as well as percent bare ground and; 2) compare the results of these cover estimates to determine the degree of agreement between the cover class estimations. For this purpose a digital technique, similar to a field-based point frame technique, was employed using a 10x10 (one pixel thick) grid overlaid upon an image to identify features beneath the grid intersection points (n=100) through visual interpretation. Features were identified as either shrub, grass, or bare ground ("S", "G", or "B"). Using these data, percent cover of shrub, grass, and bare ground was calculated. These data were also utilized to compute single factor Analysis of Variance (ANOVA). A pair-wise comparison was also performed using General Linear Model (GLM) groups, i.e., (1.00 meter per pixel [mpp] and 0.30 mpp, 1.00 mpp and 0.15 mpp, and 0.30 mpp and 0.15 mpp pixel imagery). All the percent cover estimations showed statistically significant differences ($P<0.001$) except for the bare ground comparison at 0.30 mpp and 0.15 mpp ($P=0.417$) and grasses comparison at 0.30 mpp and 0.15 mpp ($P=0.163$).

KEYWORDS: Aerial imagery, comparison study, ANOVA, General Linear Model (GLM), point frame, O'Neal ecological reserve

INTRODUCTION

In the United States of America, approximately 324 million ha are composed of rangelands (Sivanpillai and Booth, 2008). In Southeastern Idaho gentle high-desert plains exist alongside mountain ranges. The economy of this semiarid region is varied but geographically dominated by agriculture and ranching industries. For these reasons, southeastern Idaho is especially appealing for researchers concerned with the effects of drought, global climate change, and desertification on rangeland ecosystems (Sivanpillai and Booth, 2008).

Quick and accurate assessments of these diverse rangelands are imperative for sustainable management. In the past, evaluation and monitoring of expansive landscapes have relied more on judgment and experience than science (NRC 1994; Stoddart and Smith, 1995). Since conventional field survey and sampling techniques are almost impossible or impractical to implement on such a vast area, people on all sides of management issues are now calling for more quantitative monitoring approaches (NRC 1994; Donahue 1999) such as those available through remote sensing. New measures are needed, with acceptable error rates, that are cost-effective and provide timely information about those regions undergoing change (Sivanpillai and Booth, 2008; Floyd and Anderson 1987; Brady et al., 1995; Brakenhielm and Quinghong 1995).

The term remote sensing has been defined as readings and measurements that are collected from a distance without physically disturbing the object (Colwell, 1983). Remote sensing studies using satellite and aerial imagery have been used in the past to conduct studies over large areas (Blumenthal et al., 2007). Advancements in digital camera development and lens technologies have improved image sharpness up-to 1mm/pixel (Booth et al., 2006). In the past, researchers have used remote sensing techniques to study rangelands and indentify features such as invasive species, shrubs, grass, and bare ground. A study by Blumenthal (2007) used high resolution imagery to study and measure infestations of invasive terrestrial weeds. Anderson et al., (1996), Bradley and Mustard (2006), Everitt et al., (1995, and 1996) and Lass et al., (2005) suggested that satellite and aerial imagery can be used to obtain accurate results for invasive weed studies. Another study by Sivanpillai and Booth (2008) used various remote sensing techniques to determine percent cover of vegetation over the 9,000 ha Hay Press Creek Pasture near Jeffrey City, Wyoming.

The objectives of this study were to use high resolution aerial imagery (1.00 meter per pixel [mpp], 0.30 mpp and 0.15 mpp spatial resolution) to: 1) determine the percent cover of shrubs and grasses as well as percent bare ground and; 2) compare the results of these cover estimates to determine the degree of agreement between the cover class estimations. This paper is presented as a case study that may aid in the selection of future aerial imagery acquisitions, specifically those focused on the identification of land cover in semiarid rangeland.

MATERIALS AND METHODS

Study Area

Aerial imagery was collected for the O’Neal Ecological Reserve, a 50 ha area of sagebrush-steppe rangelands in southeastern Idaho approximately 30 km southeast of Pocatello, Idaho (42° 42' 25"N 112° 13' 0" W), an area where many local-scale rangeland studies are currently being conducted (Figure 1). The O'Neal Ecological Reserve (http://www.isu.edu/departments/CERE/o'neil.htm) was donated to the Department of Biological Sciences, Idaho State University by Robin O'Neal 1987. This 50 ha site, located along the Portneuf River, contains riparian areas in contrast with typical sagebrush steppe upland areas located on higher elevation lava benches. The O'Neal Ecological Reserve receives <0.38 m of precipitation annually (primarily in the winter) and is relatively flat with an elevation of approximately 1400m. The dominant plant species include big sagebrush (*Artemisia tridentata*) with various native and non-native grasses and forbs, such as Indian ricegrass (*Oryzopsis hymenoides*) and needle-and-thread (*Stipa comata*).

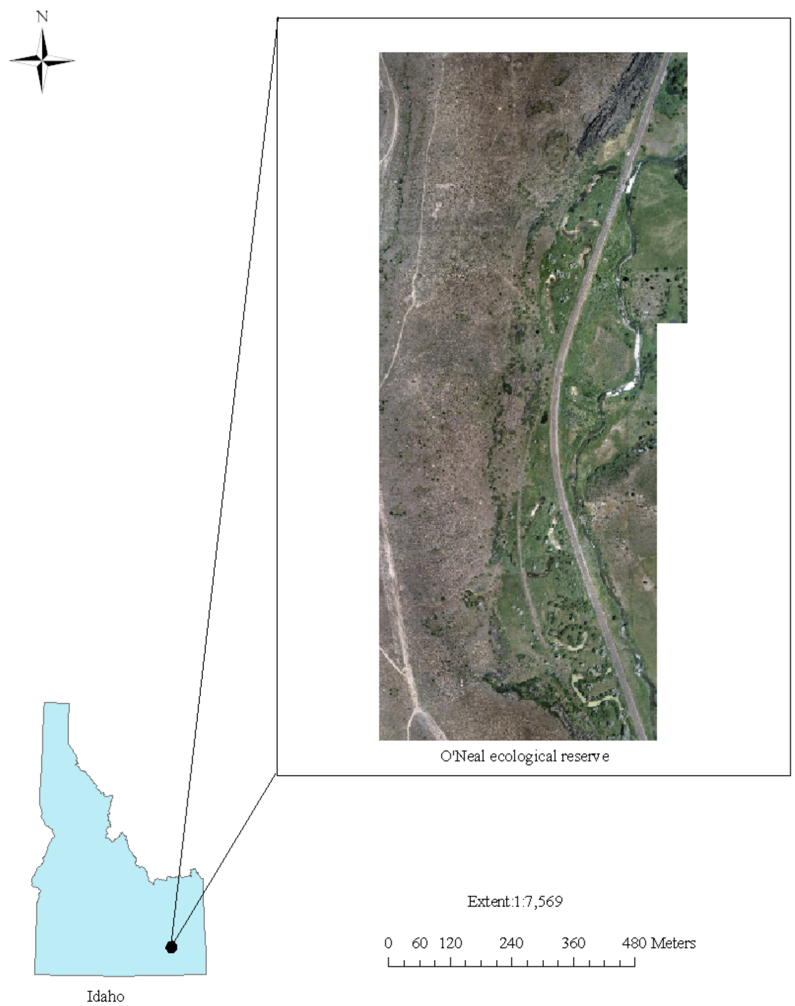

Figure 1. Area of study: O'Neal Ecological Reserve, Idaho.

Aerial imagery

National Agriculture Imagery Program (NAIP) imagery from 2004 was selected for use in this study (1 mpp). In addition 3Di West/GeoTerra Mapping Group's 2005 0.15 mpp imagery was also used. The 0.30 mpp spatial resolution image used was derived by re-sampling the 0.15 mpp using nearest neighbor algorithm. Figure 2a shows the NAIP imagery for 1.00 mpp spatial resolution, Figure 2b and Figure 2c show 0.30 mpp and 0.15 mpp spatial resolution imagery respectively.

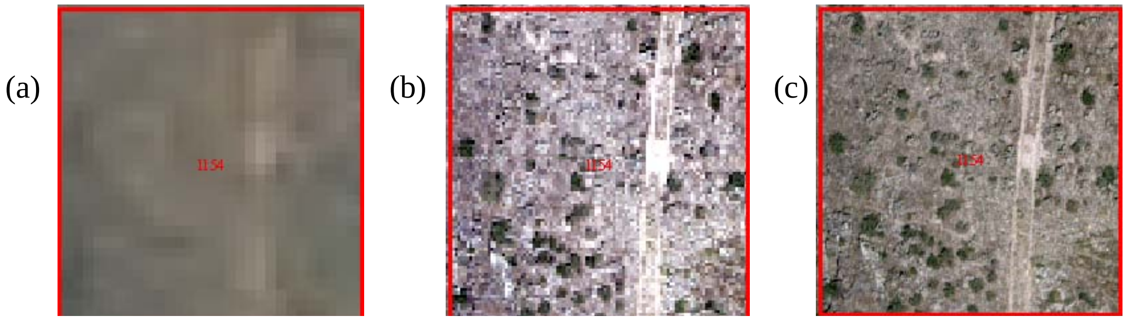

Figure 2. An example of 1.00 mpp imagery (a), 0.30 mpp imagery (b), and 0.15 mpp imagery (c) displayed at 1:500 scale.

Data Analysis

Johnson et al., (2003) created "VegMeasure" computer software that determines percent plant cover by first imposing a grid of "n" rows and "n" columns on an image. Next the information from each pixel beneath each grid is read. From there, percent cover is estimated. We developed a technique similar to "VegMeasure", for use in this study to estimate percent cover of shrubs and grasses along with percent bare ground. This point-sampling technique utilized a high resolution image that was displayed on a computer monitor near 100% magnification. Next, a grid 1-pixel thick was superimposed on the aerial image, and the cover type seen beneath each intersection (point) of the grid was manually recorded for later use (Blumenthal et al., 2007). To randomly sample the study area a shapefile containing 470 30m x 30m square polygons was created. Twenty of these polygons were randomly selected using Hawth's tools in ESRI ArcMap GIS software. The selected polygons were then extracted and saved as a new polygon shapefile. The sampling polygon shapefile was placed over the aerial imagery and all pixels inside the polygon were captured as independent TIFF files using Corel Paint Shop Pro (PSP) graphics software. This process was repeated using 1.00 mpp, 0.30 mpp, and 0.15 mpp imagery. Twenty files were collected at each spatial resolution, for an overall total of 60 files. Each image was then opened in PSP and an equi-distance grid with 10 rows and 10 columns was superimposed over the captured image (Figure3). The land cover type (shrub, grass, or bare ground ["S", "G", or "B"]) at the intersection of each horizontal and vertical line of the grid was estimated through visual interpretation.

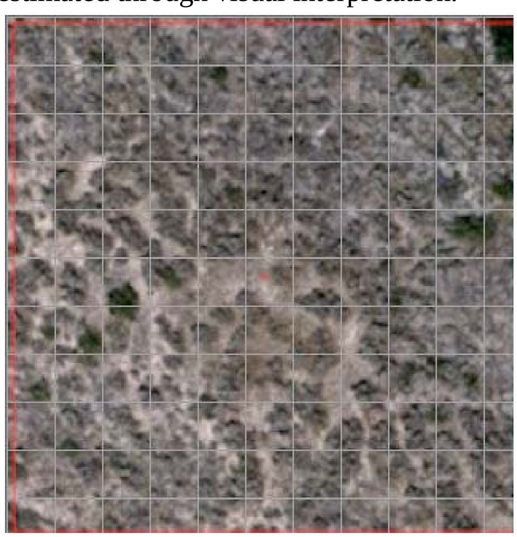

Figure 3. An example of a 10X10 grid superimposed on an image for visual interpretation (shrub, grass, bare ground) beneath each grid intersection.

This process, very similar to the field based point-frame technique ((Johnson et al., 2003; Blumenthal et al., 2007; Booth et al., 2006), was repeated for all 100 grid points in each image. The 1.00 mpp imagery was processed first, followed by the 0.30 mpp imagery and lastly, the 0.15 mpp imagery. This sequence of processing was used to reduce or eliminate biased point sampling. Following visual interpretation, a frequency distribution was created that shows the occurrences of "S", "G", and "B" within each individual image. From these data, percent cover was determined.

Statistical analysis

The percent cover of shrub, grass, and bare ground was computed using the frequency distribution for 1.0m, 0.3m and 0.15m aerial imagery. To test the precision of percent cover estimation, single factor Analysis of Variance (ANOVA) was computed between pair-wise groups (1.00 mpp and 0.30 mpp, 1.00 mpp and 0.15 mpp, and 0.30 mpp and 0.15 mpp) utilizing the percent cover for shrub, grass, and bare ground.

ANOVA can be defined as a "procedure by which the total variation in the data of the sample is split up into meaningful components that measure different sources of variation. Each of the components yield an estimate of the population variance" (Beg and Mirza, 1997). To perform a Single factor ANOVA, "independent samples each consisting of *n* observations are selected from each of K populations" (Beg and Mirza, 1997). The F-distribution values were derived from ANOVA and used to further interpret the results. The process of comparing the variability of one population with that of another population is known as F-distribution (Beg and Mirza, 1997). The P-value is the probability that ranges from 0 to 1; a lower P-value indicates that the results are less likely to occur due to random chance. The critical value established for p is the lowest level of significance at which the null hypothesis could have been accepted. In this study the null hypothesis states, "Is there a significant degree of agreement among the three different cover class estimations at the O'Neal Ecological Reserve in southeastern Idaho?"

Pair-wise comparison within General Linear Model (GLM) is a more robust statistical approach used to test whether the percent cover estimation for shrub, grass, and bare ground was different and to determine the degree of agreement between the cover class estimations at the O'Neal Ecological Reserve in southeastern Idaho. This comparison is used when one has more than two groups to compare. When H0 is rejected in an ANOVA, it is concluded that not all the means are statistically equal. This is NOT saying that all of the means are different. However, GLM Pair-wise comparisons were used to compare any two particular means using a modified 2-sample t-test to determine which means were different (Jager, 2009). The standard deviation was calculated using the Root Mean Square Error (RMSE). Using the Pair-wise comparison to compare each pair of means at $\alpha = 0.05$, some P-values will be less than 0.05 because many comparisons are made (Jager, 2009). To take care of the P-values that fall under $\alpha = 0.05$, a Bonferroni corrections was applied to the P-values to provide an adjustment factor. The Bonferroni adjusted P-values were obtained by multiplying the individual P-value by "C", where "C" is the total number of pairs of mean that has "K" population groups in an ANOVA test. C is usually computed by $C = K (K-1)/2$ (Jager, 2009). Following these methods, one can reject H0 if their P-value is $< \alpha$ (Jager, 2009).

RESULTS AND DISCUSSION

Table 1 shows the results that were obtained from single factor ANOVA. The F-values and P-values are shown in separate columns and computed for each cover class resolution pair (i.e., shrub, grass, and bare ground at 1.00 mpp, 0.30 mpp, and 0.15 mpp resolution). The analysis results using the coarsest imagery (1.00 mpp) will be discussed first, followed by comparisons made with the finer resolution imagery (0.30 mpp). The F-value for shrubs at 1.00 mpp and 0.30 mpp and 1.00 mpp and 0.15 mpp were 34.45 and 304.38, respectively. The P-values for the same comparisons were both <0.001. If we carefully observe the F-values for these two groups within the same category, i.e., shrub, we see a direct relationship between the difference in spatial resolution (e.g, 1.00 mpp and 0.30 mpp vs 1.00 mpp and 0.15 mpp) and F-values. As the difference between the spatial resolutions (1.00 mpp and 0.15 mpp) was increased, the F-value showed an increasing trend. For the grass cover class, between the groups of 1.00 mpp and 0.30 mpp and 1.00 mpp and 0.15 mpp, the F-values were 128.50 and 242.68, respectively and P-values were again <0.001. The F-values for the grass cover class showed the same direct relationship between the spatial resolution and the F-values. Similarly, for bare ground, the F-values between the 1.00 mpp and 0.3 mpp and 1.00 mpp and 0.15 mpp image resolution groups were 18.29 and 2.13, respectively, with P-values of 0.00 and 0.15, respectively. The F-values for bare ground did not follow the same direct relationship pattern as shown by shrub and grass cover classes. However, instead the F-value for this category showed an inverse pattern, i.e., the F-value decreased when the difference between the spatial resolution increased.

Table 1. ANOVA results involving 1.00 mpp imagery

ANOVA Categories	Groups	F Value *	P Value
Shrub	1.00 mpp and 0.30 mpp	34.45	<0.001
Shrub	1.00 mpp and 0.15 mpp	304.48	<0.001
Grass	1.00 mpp and 0.30 mpp	128.50	<0.001
Grass	1.00 mpp and 0.15 mpp	242.68	<0.001
Bare ground	1.00 mpp and 0.30 mpp	18.29	<0.001
Bare ground	1.00 mpp and 0.15 mpp	2.13	0.151

*NOTE: ** $F_{critical = 4.09}$

The test results for the shrub and grass cover classes show statistical significance for all comparisons computed with the 1.00 mpp and 0.30 mpp and 1.00 mpp and 0.15 mpp images (F=34.45, F=128.50). This suggests that there are many inconsistencies present in the data collected at these resolutions. These inconsistencies are present because of the visual “guessing”, i.e., errors associated with ocular estimation required to differentiate shrub, grass, and bare ground, which was based on the hue of the feature in the image (for the 1.00 mpp imagery).

The statistical data presented for bare ground (Table 1) using 1.00 mpp imagery shows F-values as 18.29, and 2.13 and P-values of 0.00 and 0.15 respectively. These values suggest that data collection was more consistent for this cover class. Alternatively, these values may represent a statistical anomaly or may be because bare ground was more easily detected at all three spatial resolutions. To test this, a second iteration of analysis based on the hue of the feature could be repeated using new polygon sample sites. This was not done due to the time constraints in this study.

Table 2 shows the statistical data for the shrub cover class at 0.30 and 0.15 mpp resolutions. The F-value for this comparison was 70.55 with a P-value of <0.001. This suggests that the shrub cover class percent cover estimation at resolutions of 0.30 mpp and 0.15 mpp was not consistent. The F-value for the shrub cover class showed a direct relationship between the difference in spatial resolution and F-values. As the difference between the spatial resolutions (e.g, 0.30 mpp and 0.15 mpp) increased the F-value increased as well (F=70.55). The statistical comparison for the grass cover class at 0.30 mpp and 0.15 mpp results in an F-value of 2.28 and a P-value of 0.13. This indicates that the grass cover class estimates at 0.30 mpp and 0.15 mpp resolution were consistent as no statistical difference was found. Further, the F-value for the grass cover class did not follow the same trend as the shrub cover class, i.e., as the difference between the spatial resolutions (0.30 mpp and 0.15 mpp) was increased the F-value decreased (2.28).

Table 2. ANOVA results involving 0.15 mpp imagery

ANOVA Categories	Groups	F Value *	P Value
Shrub	0.30m and 0.15m	70.55	<0.001
Grass	0.30m and 0.15m	2.28	0.138
Bare ground	0.30m and 0.15m	38.74	<0.001

*NOTE: ** $F_{critical = 4.09}$

However, when comparing bare ground at relative fine resolutions (0.30 mpp and 0.15 mpp), the consistency was lost as the F-value was 38.74 (P-value = <0.001). Bare ground showed the same trend of F-value found in shrub cover class, i.e., as the difference between the spatial resolutions (0.30 mpp and 0.15 mpp) increased the F-value also increased. The P- and F-values for grass differ from the P- and F-values for shrubs and bare ground indicating that a statistical anomaly for grass cover class was present or, perhaps bare ground was more easily detected at all three spatial resolutions. These results were also consistent with the reality, for example, if individual grains of sands were observed, at that scale, it is still bare earth. If shrubs and grass were looked at the same scale then nothing would detectable.

Table 3 shows the pair-wise statistical comparison for shrub cover class using (1.00 mpp, 0.30 mpp, and 0.15 mpp resolutions. The first column of table 3 shows the resolutions as input data. The second column shows the difference of means in percent cover calculated for the two resolutions. The third column shows the standard error, representing the standard deviation describing the dispersion of data points above and below the regression line (Weiers, 1998). The fourth column shows whether the test results for shrub percent cover estimates were statistically significant or not. The fifth and sixth columns describe (lower bound and upper bound) percent cover values that lies on a normal curve. The lower bound value lies on the left side of the mean whereas the upper bound value lies on the right side of the mean, assuming the data follow normal distribution. However, the percent cover estimation values did not follow a normal distribution as the Kurtosis values for shrub, grass and bare ground were not equal to three and Skewness values were greater than zero.
The GLM Pair-wise comparison was done on the same resolutions group. For example, GLM pair-wise comparison between 1.00 mpp and 0.30 mpp yields a “Mean Difference (I-J)” of “-20.30”, a standard error of “4.07”, Significance value of “0.00” with a lower and upper bound of “-30.99” and “-9.60” respectively. The significance value of “0.00” suggests that there is no agreement between the two cover

class estimates for shrub. Similarly, all of the different resolution data for shrub was compared against each other. These results also suggest that the percent cover estimation was not consistent. Table 3 results are also consistent with the results computed in table 2, utilizing simple ANOVA for shrub.

Table 3. GLM Pair-wise comparison of percent cover of shrubs using 1.00 mpp, 0.30 mpp, and 0.15 mpp imagery

(I) resolution	(J) resolution	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	Upper Bound
1.00 mpp	0.30 mpp	-20.300*	4.073	.000	-30.992	-9.608
	0.15 mpp	-53.300*	2.829	.000	-60.725	-45.875
0.30 mpp	1.00 mpp	20.300*	4.073	.000	9.608	30.992
	0.15 mpp	-33.000*	4.499	.000	-44.811	-21.189
0.15 mpp	1.00 mpp	53.300*	2.829	.000	45.875	60.725
	0.30 mpp	33.000*	4.499	.000	21.189	44.811

**. The mean difference is significant at the 0.05 level.*
a. Adjustment for multiple comparisons: Bonferroni.

Table 4 shows the GLM Pair-wise comparison for grass cover using 1.00 mpp, 0.30 mpp, and 0.15 mpp resolutions. The GLM Pair-wise comparison was done on these different resolution groups for percent cover estimates. For example, the pair-wise comparison between the group of 1.00 mpp and 0.30 mpp yields a “Mean Difference (I-J)” of “43.40”, a standard error of “2.94”, Significance value of “0.00” with a lower and upper bound of “35.67” and “51.12” respectively. A significance value of “0.00” describes that there is no agreement between the two cover class estimates for grass. Similarly all the different percent cover class estimates from different resolutions for grass cover class were compared against each other. These results suggests that the percent cover estimates were not consistent, except for the comparison of 0.30 mpp and 0.15 mpp and 1.00 mpp and 0.15 mpp percent cover estimates that suggests a consistent pattern. The consistency between these two groups might be the result of a statistical anomaly for grass cover class that had occurred. Table 4 results were also consistent with the results computed in table 2 utilizing simple ANOVA for grass.

Table 5 shows the GLM Pair-wise comparison for bare ground cover class using 1.00 mpp, 0.30 mpp, and 0.15 mpp resolutions. The GLM Pair-wise comparison was performed using these different resolution groups for percent cover estimates. For example, the Pair-wise comparison between the group of 1.00 mpp and 0.30 mpp yields a “Mean Difference (I-J)” of “-21.95”, a standard error of 4.52, a significance value of “0.00” with a lower and upper bound of “-33.82” and “-10.07” respectively. The significance value of “0.00” suggests that there is no agreement between the two cover estimations collected at different spatial resolutions for bare ground. Similarly all different percent cover class estimates from different resolutions for bare ground cover class were compared against each other. These results also suggests that the percent cover estimates were not consistent except for the results produced from the comparison of 1.00 mpp and 0.15 mpp and 0.15 mpp and 1.00 mpp percent cover estimates, suggesting a consistent pattern. The consistency between these two groups might be the result of a statistical anomaly for bare ground cover class that had occurred. Table 5 results were also consistent with the results computed in table 2 utilizing simple ANOVA for bare ground.

Table 4. GLM Pair-wise comparison of percent cover of grass using 1.00 mpp, 0.30 mpp, and 0.15 mpp imagery

(I) resolution	(J) resolution	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	Upper Bound
1.00 mpp	0.30 mpp	43.400*	2.943	.000	35.675	51.125
	0.15 mpp	47.350*	2.605	.000	40.512	54.188
0.30 mpp	1.00 mpp	-43.400*	2.943	.000	-51.125	-35.675
	0.15 mpp	3.950*	1.927	.163	-1.108	9.008
0.15 mpp	1.00 mpp	-47.350*	2.605	.000	-54.188	-40.512
	0.30 mpp	-3.950*	1.927	.163	-9.008	1.108

**. The mean difference is significant at the 0.05 level.*

a. Adjustment for multiple comparisons: Bonferroni.

Table 5. GLM Pair-wise comparison of percent cover of bare ground using 1.00 mpp, 0.30 mpp, and 0.15 mpp imagery

(I) resolution	(J) resolution	Mean Difference (I-J)	Std. Error	Sig.[a]	95% Confidence Interval for Difference[a] Lower Bound	Upper Bound
1.00 mpp	0.30 mpp	-21.950*	4.523	.000	-33.823	-10.077
	0.15 mpp	5.950	3.854	.417	-4.166	16.066
0.30 mpp	1.00 mpp	21.950*	4.523	.000	10.077	33.823
	0.15 mpp	27.900*	5.081	.000	14.561	41.239
0.15 mpp	1.00 mpp	-5.950*	3.854	.417	-16.066	4.166
	0.30 mpp	-27.900*	5.081	.000	-41.239	-14.561

**. The mean difference is significant at the 0.05 level.*

a. Adjustment for multiple comparisons: Bonferroni.

The F-statistic for each comparison (1.00 mpp and 0.30 mpp, 1.00 mpp and 0.15 mpp, and 0.30 mpp and 0.15 mpp) of Table 1 and Table 2 was graphed (Figure 4) to better illustrate and visualize the results of the statistical analyses. On the x-axis are the resolution groups compared with F-distribution values given on the y-axis. The F-critical (i.e., F = 4.09) is shown to visualize which cover class fell below the critical region. The critical region is the region wherein the hypothesis statement made for the analysis is rejected, and one needs to consider the alternative of the statement (Beg and Mirza, 1997). All F-values in Table 1 for shrub and grass fall outside of the critical region suggesting that the percent cover estimates were different. However, the ANOVA for 1.00 mpp and 0.15 mpp for bare ground has F-value = 2.13, suggesting that the percent cover estimate was consistent. Similarly in Table 2, shrub and bare ground cover classes for 0.30 mpp and 0.15 mpp suggest that the percent cover estimate was not consistent as the F-value lies outside the critical region (i.e. $F_{critical} =$ 4.09). The F-value in table 2 suggests that the percent cover estimate was consistent as the F-value (i.e., F = 2.28) lies inside the critical region value.

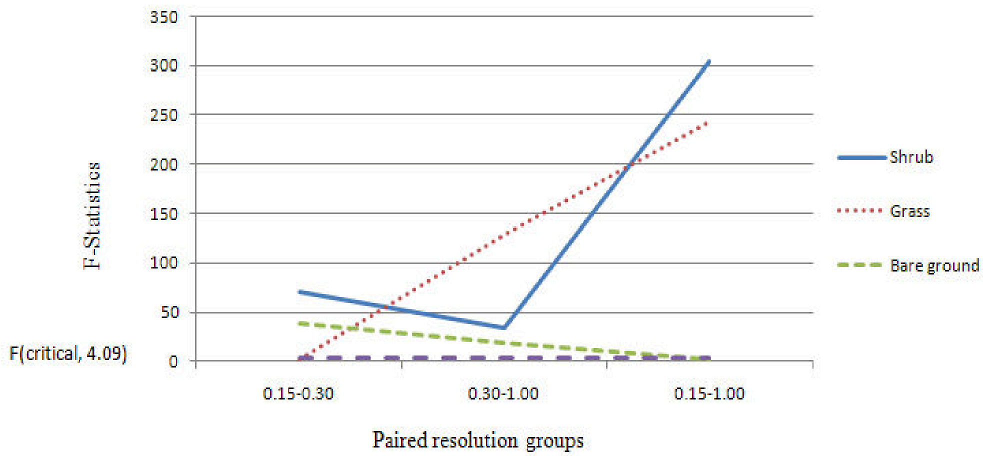

Figure 4. F-distribution plot for shrub, grass, and bare ground with F-critical values.

Assessment of Error and bias

Although much care was taken in the collection of samples from the aerial imagery there were a number of errors and biases worth noting. The 1.0m imagery used for sampling did not have sufficient resolution to see discernible plant features, but instead all decisions to indentify shrub, grass, and bare ground were made on the basis of the color or hue present in the image. NAIP imagery was shot in 2004 and 3Di West imagery was shot in 2005, therefore, what details that were seen in 2004 might have changed by the time imagery was shot in 2005. The time of year when images were acquired might have also provided error or bias in the results. The images may have been collected in early spring for one year and/or early fall for another year. This would introduce seasonal vegetation variety, a factor we did not account for in our study. In addition, the aerial images were not collected in the same year, so what was identified as shrub in one set of imagery might have changed. Lastly, the field condition itself We do not know which resolution actually gave the correct answer as no field data are available for either time period. Field information would clarify such distinctions as what was identified as shrub might actually be a hole in the ground, or what was identified as bare ground could actually be a reflective piece of metal lying on the ground. Still, our information is based on the best data we could obtain for this study.

CONCLUSIONS

Range scientists usually express cover as the percentage of the ground surface that is occupied by the plant crown or shoot area when it is projected downward (Johnson et al. 2003). The percent cover of shrub, grass, and bare ground can be estimated using point frames**,** quadrant charting, line intercept transect or other techniques. This study employed a digital technique, similar to the point frame technique, and used a 10x10 (one pixel thick) grid superimposed upon an image to identify features beneath the grid intersection points. The results were compared statistically for shrub, grass, and bare ground cover classes using ANOVA and GLM Pair-wise comparison. The ANOVA results for 1.00 mpp imagery shows that the percent cover estimates for the shrub and grass were not consistent, however, the bare ground percent cover estimates show a consistent pattern. The ANOVA result for 0.15 mpp imagery for shrub and bare ground shows inconsistency in the percent cover estimates, but the F-value for grass indicates that the percent cover estimation was consistent. The GLM Pair-wise comparison results for shrub, grass, and bare ground using 1.00 mpp, 0.30 mpp, and 0.15 mpp pixel imagery showed results similar to those produced by ANOVA. Overall percent cover estimations were not consistent across spatial resolutions or cover classes. This means that the percent cover estimation using three spatial resolutions (1.00 mpp, 0.30 mpp, and 0.15 mpp) differs from each other. Some statistical anomalies did occur in the study that suggests that the percent cover estimation for bare ground and grass were the same. To test this, a second iteration of analysis based on the hue of the feature could be repeated using new polygon sample sites. This was not done due to the time constraints in this study. Further research should be conducted by first surveying the field and then by using the HRSI of the same year.

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Investigating the Utility of SPOT Multispectral Imagery for Forage Estimation on a Rangeland Site in Southeastern Idaho

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ABSTRACT

Field- or ground-based estimates of forage availability can be time consuming and fraught with errors due to the inherent heterogeneity found in semiarid rangelands. Satellite remote sensing offers the potential to improve forage estimation by incorporating rangeland variability into the modeling process by developing estimates based upon each and every pixel. The problem with this approach however, is that pixels are typically too large to offer meaningful results and the heterogeneity within each pixel can make forage estimation with remote sensing techniques just as difficult as using ground-based measures or estimates. While the size of MODIS pixels (1000m x 1000m) is admittedly too coarse for forage availability modeling, SPOT5 pixels (10m x 10m) may be sufficiently resolved to provide accurate forage estimations. To test this, a study was designed and is described in this paper. The results of this study suggest that reliable forage estimation with remotely sensed imagery will require spatial resolutions better than offered by the SPOT 5 sensor as the coefficient of determination (R2) did not exceed 0.18 with any band combination tested.

KEYWORDS: semiarid rangelands, NDVI, SAVI, NDSAVI

INTRODUCTION

Ground-based forage estimation can be a tedious effort especially in semi-arid rangelands due to large, expansive area and the uncertainty of prediction that arises when working in these heterogeneous landscapes. Nonetheless, biomass and especially forage estimates are some of the "main parameters used in range management" (Tueller 2001). While, remote sensing techniques have proven useful for estimating general biomass values over large areas (Tueller 2001; Wylie et al. 2002), the utility of remote sensing for estimating *only* the available forage as a component of total biomass has proven much more difficult. However, with state-of-the-art satellite imagery, the potential exists to accurately model forage. This study was designed to determine how well SPOT multispectral imagery (10 x 10 m pixels) could estimate available forage at the ISU O'Neal Ecological Reserve located near McCammon, Idaho using both simple regression and supervised classification techniques.

METHODS

Data Collection

A ground-based survey conducted during July 2006 resulted in 145 stratified random sample plots, each measuring 10 x 10 m. At each plot center point, vegetation considered adequate forage for cattle, sheep, and wild ungulates was determined using a $0.44 m^2$ hoop that was randomly tossed into each of four quadrants (NW, NE, SE, and SW) centered over the sample point. Forage within the hoop was clipped and weighed (+/-1g) using a Pesola scale tared to the weight of an ordinary paper bag (all grass species, except cheatgrass (*Bromus tectorum*) were considered forage). The measurements were then used to estimate forage amount in AUM's, pounds per acre, and kilograms per hectare (Sheley et al., 1995). The location and forage information of each sample plot was collected using a Trimble GeoXT GPS receiver with Windows Mobile PocketPC capable of sub-meter horizontal positional accuracy (+/- 0.9m @ 95% CI (Serr et al., 2007). These data points were saved in ESRI shapefile format.

Also, SPOT imagery was acquired on July 11, 2006. This imagery had 10 X 10 m pixels with reflectance measured in four visible wavebands (near infrared, red, green, and short-wave infrared). The imagery was geo-rectified and atmospherically corrected. Various vegetation indices were calculated using the SPOT imagery including normalized difference vegetation index (NDVI), normalized difference senescent vegetation index (NDSVI) (Qi and Wallace 2002), soil-adjusted vegetation index (SAVI) and a ratio-type index derived from the short-wave infrared band (SWIR) divided by the green band (Wylie et al. 2002). Calculation of these indices was accomplished using IDRISI Andes software (Clark Labs, Clark University, Worcester, MA).

Regression Analyses

Simple linear regressions were performed to evaluate the relationship between vegetation indices and the field-based forage measurements.

Supervised Classification

Supervised classification of the SPOT imagery was performed using a shapefile describing the forage measurements taken in the field. The mean of the four forage measurements taken at each point was used to represent forage availability at each point. A histogram was tabulated for all of the available data points and 10 classes were determined. Each p-quantile (probability) was used to re-bin the data (0.1 to 1.0). The final binning is shown in Table 1. This binning was done with understanding that if each individual forage estimate were treated as a specific class, the supervised classification results would be poor. For example, the classification algorithm would find difficulty in discriminating classes with very similar forage estimates. Each p-quantile from the cumulative distribution frequency of the forage data gave a reasonable number of data points for each class. This shapefile was randomly subsampled without replacement and 65 % (n= 94) of the points were reserved as training sites while the remaining 35 % (n=51) of points were used as validation sites. These points were rasterized using ArcMap (ArcGIS 9.1, ESRI) for use in IDRISI Andes. All classification procedures were performed in IDRISI Andes.

Table 1. Binning strategy for determining classes for supervised classification. Each p-quantile from the cumulative distribution frequency of the forage data gave a reasonable number of data points for each class.

Approx. p-quantile	Forage range (kg/ha)	Class
0.1	1-15	1
0.2	16-21	2
0.3	22-27	3
0.4	28-38	4
0.5	39-50	5
0.6	51-65	6
0.7	66-80	7
0.8	81-100	8
0.9	101-150	9
1.0	151-300	10

Maximum Likelihood Classification

Maximum likelihood is “a statistical description of the manner in which expected landcover classes should appear in the imagery, and then a procedure is used to evaluate the likelihood that each pixel belongs to one of these classes” (Eastman 2006). First, spectral signatures were created (extracted) from the training sites (field forage measurements) using the MAKESIG module. All SPOT spectral bands and the vegetation indices (NDVI, SWIR/Green, NDSVI, and SAVI) were chosen as the bands to extract spectral data from. The SIGSOMP module was then used to evaluate where, if any, differences occur between the training site input bands. As high correlations existed between many of the raster layers, there was difficulty encountered separating the spectral signatures. Therefore, principal components analysis (PCA) was performed to better capture the unique data within the input bands. The actual classification was done using the MAXLIKE module. Probabilities of each class were set to equal and the signature file created above using PCA was used. Lastly, an accuracy assessment of the classification was performed using the ERRMAT module which produces an error matrix of the input classification model. This matrix reports user and producer accuracies and errors. A kappa index of agreement (KIA) is also reported.

Classification Tree Analysis

Classification tree analysis (CTA), also called decision tree analysis, has leaves and branches where leaves represent classifications and branches represent “conjunctions of features that lead to those classifications” (Eastman 2006). Basically speaking, the software splits each pixel into probabilities of belonging to a certain class until a statistical threshold is reached and a decision is made to what class the pixel belongs. CTA has been reported to achieve consistently better accuracy than Maximum Likelihood (Frield and Brodley, 1997). Classification tree analysis (CTA) was carried out using the same basic tenets in maximum likelihood above by using the principal component images (from PCA). Error assessment techniques were used to evaluate classification performance as described above.

RESULTS AND DISCUSSION

Regression analysis

The regressions proved to be very limited in uncovering any valuable information regarding forage estimation. Figure 1 shows the correlations between each vegetation index and field forage measurements. It has been recently reported that a simple ratio vegetation index of the short-wave infrared spectral band (SWIR) divided by the green spectral band is a good estimator of forage (Mirik et al. 2005). In comparison with the regression results, this vegetation index did report the highest R^2 value (0.1796). A full comparison of the R^2 values can be seen in Table 2.

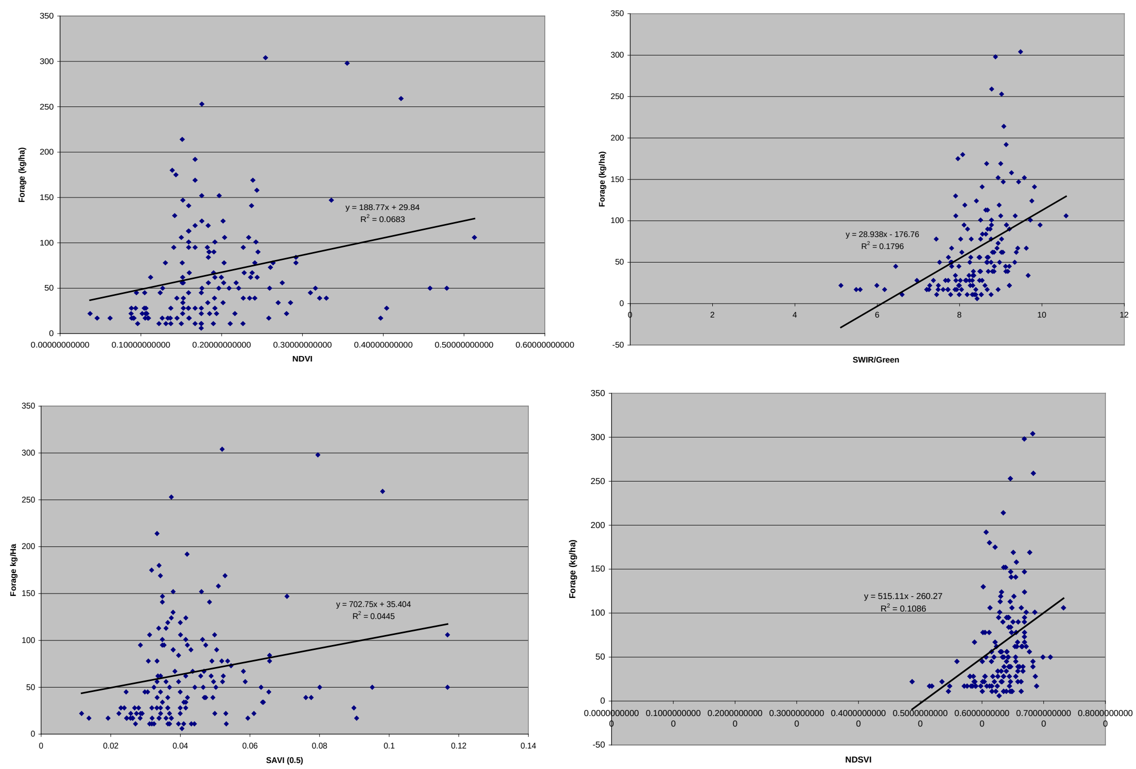

Figure 1. Linear regressions of different vegetation indices and forage estimates. Starting with the top left graph and continuing clockwise: NDVI, SWIR/Green, NDSVI, SAVI.

Table 2. Reported R^2 value of each vegetation indices correlated with forage estimates.

	NDVI	SWIR/Green	SAVI	NDSVI
Reported R^2	0.0683	0.1796	0.0445	0.1086

Maximum Likelihood Classification

Maximum likelihood classification performed poorly. The kappa index of agreement (KIA) was reported as 0.0385. Congalton (1991) suggests that a KIA of 0.60 or higher is needed to express statistical significance in relation to a classified geographic model. It was concluded that maximum likelihood also proved to be a poor estimator of available forage given the methods presented in this study.

Classification Tree Analysis

More hope was given to classification tree analysis (CTA) as it has been reported to frequently give better results that maximum likelihood classification. The CTA model is shown in Figure 2.

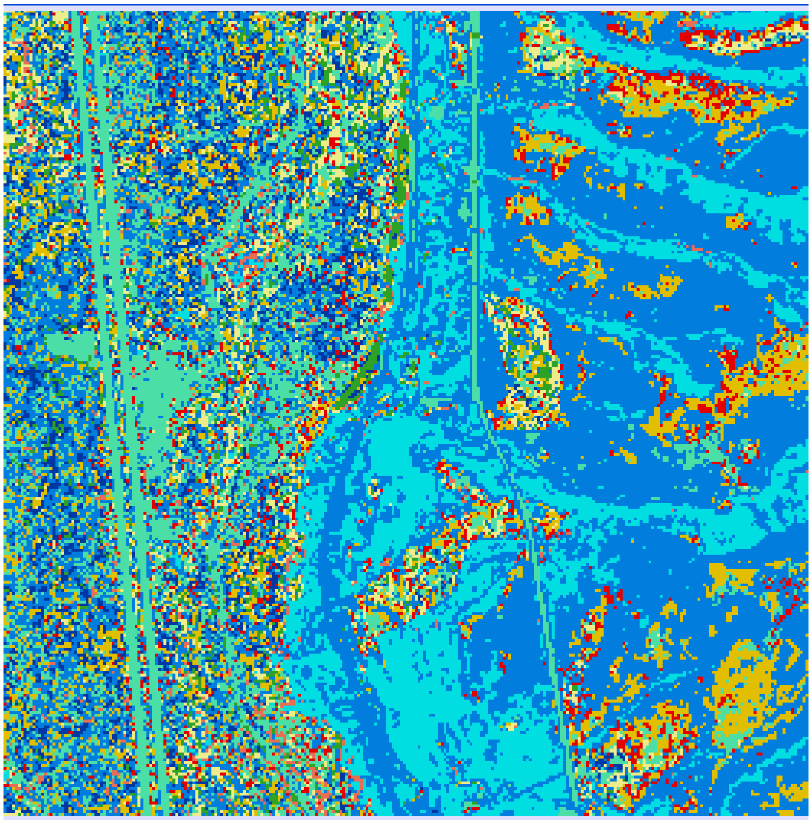

Figure 2. Forage estimation using classification tree analysis for the O'Neal Ecological Reserve and surrounding area.

CTA also proved limited in modeling forage availability (Table 3).

Table 3. Error matrix describing results of classification tree analysis (CTA)

```
Error Matrix Analysis of VS_CAT_GOOD1 (columns : truth) against CTA_CAT_1 (rows : mapped)

              1          2          3          4          5
        ----------------------------------------------------
    1 |       7          5          0          1          0     0.5000
    2 |       5          4          2          1          3     0.7647
    3 |       1          0          2          2          0     0.7143
    4 |       0          1          1          0          0     1.0000
    5 |       0          2          0          1          0     1.0000
    6 |       0          0          0          2          0     1.0000
    7 |       1          1          1          0          2     1.0000
    8 |       1          0          0          0          0     1.0000
    9 |       0          0          0          0          0
        ----------------------------------------------------
Total |      15         13          6          7          5
ErrorO |  0.5333     0.6923     0.6667     1.0000     1.0000

              7          8          9      Total     ErrorC
        ----------------------------------------------------
    1 |       0          1          0 |       14     0.5000
    2 |       1          0          1 |       17     0.7647
    3 |       1          0          1 |        7     0.7143
    4 |       0          0          0 |        2     1.0000
    5 |       0          0          0 |        3     1.0000
    6 |       0          0          0 |        2     1.0000
    7 |       0          0          0 |        5     1.0000
    8 |       0          0          0 |        1     1.0000
    9 |       0          0          0 |        0
        ----------------------------------------------------
Total |       2          1          2 |       51
ErrorO |  1.0000     1.0000     1.0000 |                 0.7451


         ErrorO     = Errors of Omission   (expressed as proportions)
         ErrorC     = Errors of Commission (expressed as proportions)

         90% Confidence Interval  =  +/-  0.1004    (0.6447 - 0.8455)
         95% Confidence Interval  =  +/-  0.1196    (0.6255 - 0.8647)
         99% Confidence Interval  =  +/-  0.1574    (0.5877 - 0.9025)

KAPPA INDEX OF AGREEMENT (KIA)
------------------------------

Using CTA_CAT_1 as the reference image ...

    Category          KIA
------------      ------------

           1       0.2917
           2      -0.0263
           3       0.1905
           4      -0.1591
           5      -0.1087
           6       0.0000
           7      -0.0408
           8      -0.0200
           9       0.0000

VS_CAT_GOOD1

    Category          KIA
------------ ------------

           1       0.2649
           2      -0.0385
           3       0.2273
           4      -0.0408
           5      -0.0625
           7      -0.1087
           8      -0.0200
           9       0.0000

Overall Kappa =          0.0718
```

Based upon KIA, CTA proved to be marginally better for modeling forage availability as opposed to maximum likelihood classification (0.0718 vs. 0.0385, respectively), however, Congalton (1991) notes that this level of KIA can be purely achievable through chance agreement alone. Figure 4 summarizes a regression of the validation sites as compared to the CTA. In the case of perfect 100% agreement (KIA = 1.0), the points plotted in Figure 4 would fall along a 1:1 line. The reported r value was -0.002185, highlighting the weakness of this model for forage estimation in this study.

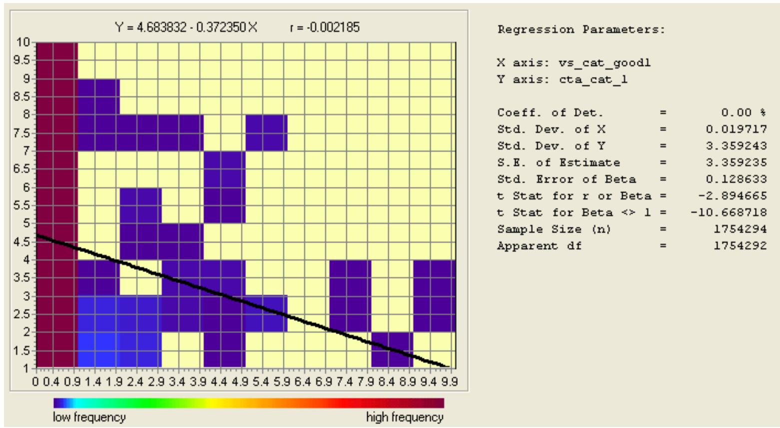

Figure 3. Regression of validation sites used for the forage estimation classification tree analysis.

CONCLUSIONS

Modeling forage availability using SPOT satellite imagery proved exceedingly difficult. Although disappointing, this result is not entirely surprising given the understanding that forage reflectance on a pixel-by-pixel basis is only a small component of the total reflectance signature for that pixel. The authors note that these field data were collected in July which is a time period when many if not all of the grasses are senescing. This alone could help explain why the NDSVI proved to report a marginally better R^2 value than other indices save for the biomass index (SWIR/GREEN).

Land managers rely on estimates of forage to help make decisions regarding stocking rates, wildlife conservation, and desertification issues. While the authors believe it would be worthwhile to continue to evaluate the utility of the methods presented in this paper (perhaps using imagery collected during different time periods such as before cattle grazing begins or before the senescence of grasses), these techniques are not currently reliable for management purposes.

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Correlation between MODIS LAI, GPP, PsnNet, and FPAR and Vegetation Characteristics of Three Sagebrush-Steppe Sites in Southeastern Idaho

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ABSTRACT
The Moderate Resolution Imaging Spectroradiometer (MODIS) has been used for vegetation monitoring and mapping since February 2000. However, few studies have been conducted that corroborate MODIS data with *in situ* field observations. This study explores the relationship between MODIS products (Leaf area index, gross primary productivity, net Photosynthesis, and fraction of absorbed photosynthetically active radiation) and percent cover and plant biomass for three sagebrush-steppe rangeland sites in southeastern Idaho. Correlations were calculated using data collected between June 2007 and August 2007 with resulting correlation coefficients being very weak in all cases ($R^2 \leq 0.09$). Two of the three sites tested were correlated with percent cover estimates calculated from point intercept transect data while the remaining site was correlated with ocular estimated cover classes. Even though transect data is considered to more precisely describe field plots, their correlations with the MODIS products did not improve relative to the correlations made with ocular estimates. While the spatial distribution of the field observations and various other factors may have affected these results, no significant correlations are expected to emerge due primarily to differences in scale between these data.

KEYWORDS: remote sensing, vegetation monitoring, productivity

INTRODUCTION

The Moderate Resolution Imaging Spectroradiometer (MODIS) is an instrument specifically designed for improved remote sensing of the land, seas, and the atmosphere. The sensor for land imaging integrates the characteristics of the Advanced Very High Resolution Radiometer (AVHRR) and the Landsat Thematic Mapper. The spatial resolution of the sensor varies from 250 m (bands 1 and 2), to 500 m (bands 3-7), and 1000 m (bands 8-36)(Justice et al 1998; http://modis.gsfc.nasa.gov/about/specifications.php).
MODIS has been widely used for land cover classification since February 2000 because of its enhanced spectral (bandwidth 620-965 nm and 3.6 to 14.3 µm), spatial (250 m to 1000 m resolution at nadir), and temporal (daily to 8-day products) resolution. Further, MODIS enables improved monitoring and mapping of global land cover compared to that offered by AVHRR (Friedl et al 2002) and these studies are important to increasing our understanding of global climate and biogeochemical cycles (Running et al 1994).

Biological productivity is the ultimate source of human civilization; hence accurate estimates of various vegetation parameters (cover and productivity) are increasingly important to our understanding of the carbon cycle, energy balance, environmental impact assessment studies (Tian et al 2000) as well as the effect of global climate change. MODIS provides an array of products that estimate vegetative productivity. The MODIS algorithms use photosynthetically active radiation (PAR) and its relationship with net primary productivity (NPP) to develop a variety of MODIS products. Some of the PAR is absorbed by the vegetation and is known as absorbed photosynthetically active radiation (APAR). APAR is a function of the spatial and seasonal variability of photoperiod, potential incident radiation, and the amount and geometry of displayed leaf material. It is similar to LAI but accommodates the fraction of absorbed photosynthetically active radiation (FPAR) to help define the relationship of APAR and PAR as APAR = PAR * FPAR. The PAR conversion efficiency (ε) is dependent upon vegetation type and can be combined with APAR to estimate gross primary productivity (GPP) as:
$GPP = \varepsilon * APAR$ (1)

GPP describes the total light energy that has been converted to plant biomass. Some of the energy is lost during plant respiration and this fraction can be derived from GPP. The MODIS product which describes the relationship between GPP and the fraction of energy lost during plant respiration is called net primary productivity (NPP). Yet another MODIS product calculates net photosynthesis (PsnNet) by subtracting leaf maintenance respiration and fine root mass maintenance respiration from GPP (Running et al 1999), while green leaf area index (LAI) - along with FPAR- represents differences in leaf nitrogen content (Heinsch et al 2003).

While MODIS products provide valuable estimates of vegetation productivity, it is important to validate these products with *in situ* measurements. However, uncertainty assessments for coarse resolution satellite imagery presents a host of challenges as field data is not easily compared with satellite imagery (Tian et al 2002). Tian et al (2002) presented a validation method of the MODIS LAI product with emphasis on the sampling strategy for field data collection. They suggest a statistically valid and logistically feasible sampling strategy which would reduce uncertainty based on a hierarchical analysis of LAI obtained from 30 m resolution Landsat ETM+ data. Variance calculations are made for LAI and NDVI with respect to class effect, region effect, and pixel effect (Tian et al 2002).

The validation methods developed by Tian et al is indirect (i.e., they validate one satellite dataset [MODIS] with another satellite dataset [Landsat] with the underlying assumption of accuracy for the Landsat dataset) but other studies have established more direct correlations of MODIS products with ground based data. Barnsley et al (2000) used a model to predict albedo, a parameter that involves understanding both climate and vegetation dynamics, to validate the corresponding MODIS albedo product. In addition, Fensholt et al (2004) studied MODIS LAI and FPAR and the relationship between FPAR and NDVI in a semi-arid environment using *in situ* measurements. They concluded that MODIS LAI was overestimated by approximately 2–15% and the overall level of FPAR was overestimated by 8–20%.

This author's study validates MODIS LAI, GPP, PsnNet, and FPAR products by direct comparison with *in situ* data obtained from three different sagebrush-steppe rangeland sites in southeastern Idaho.

METHODS

Study Area

Three sagebrush-steppe rangeland sites in southeastern Idaho were chosen for this validation study: the USDI BLM Big Desert (Big Desert), USDA ARS US Sheep Experiment Station (USSES), and the ISU O'Neal Ecological Reserve (O'Neal). Each of these sites is part of ongoing rangeland research at the GIS Training and Research Center (GIS TReC) at Idaho State University.

The Big Desert is the largest of the three study sites containing approximately 100,000 ha managed by the Bureau of Land Management (BLM). The area is flat to slightly rolling with abundant lava outcrops. The average annual precipitation in the area is 0.23 m with only 40% falling from April to June (Connelly et al 1991). The Big Desert exhibits a large variety of native plant species as well as numerous invasive species (Anderson et al 2008). The dominant vegetation species in this study area are Wyoming Big Sagebrush (*Artemisia tridentataWyomingensis*) and bluebunch wheatgrass (*Pseudoroegneria spicata*). Other species present are threetip sagebrush (*Artemisia tripartita*), Sandberg bluegrass (*Poa secunda*), and bottlebrush squirreltail (*Sitanian hystrix*) (Fischer et al 1991).

The USSES study site includes nearly 40,000 ha of rangeland with mean annual precipitation significantly changing as site elevation ranges from 1615 to 2900 m. The dominant plant species are Mountain Big Sagebrush (*Artemisia tridentata*), threetip sagebrush (*Artemisia tripartita*), Antelope bitterbrush (*Purshia tridentata*), bluebunch wheatgrass (*Pseudoroegneria spicata*), thickspike wheatgrass (*Elymus lanceolatus*), Sandberg bluegrass (*Poa secunda*), arrowleaf balsamroot (*Balsamorhiza sagittata*), and tapertip hawksbeard (*Crepis acuminata*) (Weber et al 2008).

The O'Neal study site is a 50 ha area along the Portneuf River. This area receives < 0.38 m of precipitation every year and its elevation ranges between 1400 m to 1430 m. The dominant plant species of the area are Big sagebrush (*Artemisia tridentata*) along with other native and non-native grasses that include Indian rice grass (*Oryzopsis hymenoides*) and needle-and-thread (*Stipa comata*) (Weber et al 2007) (Figure 1).

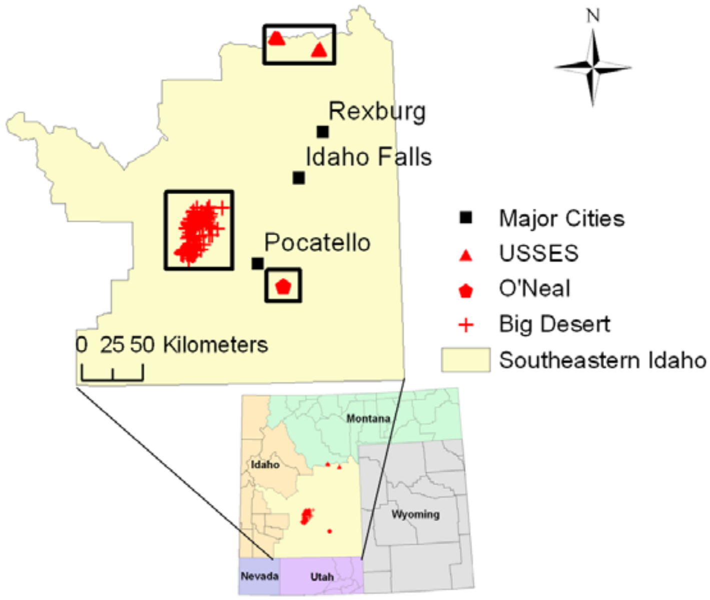

Figure 1. Location of the Three Study Sites in Idaho

Field Sampling Procedures

During the summer of 2007 GIS TReC field personnel collected vegetation data at each of the three study sites. These data (*n*= 347) include ocular estimates for percent cover of grasses, shrubs, litter, weeds, and bare ground at the Big Desert study site, while more precise estimates of percent cover for grasses, shrubs, litter, weeds, and bare ground were made using point-intersect transects at both the USSES and O'Neal sites.

The location of each sample site was recorded using a Trimble GeoXH GPS receiver in latitude-longitude (WGS 84). Points were occupied until a minimum of 60 positions were acquired and the Wide Area Augmentation System (WAAS) was used whenever available. All points were post-process differentially corrected (+/-0.20 m with a 95% CI) using an array of southeastern Idaho GPS base stations each located <80 km from the respective study area. All sample points were projected into Idaho Transverse Mercator NAD 83, using ESRI's ArcGIS (Anderson et al., 2005). These data were stored as three independent feature classes.

Ground Cover Estimation

Visual estimates were made of percent cover for the following; bare ground, litter and duff, grass, shrub, and dominant weed. Cover was classified into one of nine classes (None, 1-5%, 6-15%, 16-25%, 26-35%, 36-50%, 51-75%, 76-95%, and >95%).

Observations were assessed by viewing the vegetation perpendicular to the earth's surface. This was done to emulate what a "satellite sees". In other words the vegetation was viewed from nadir (directly overhead) as much as possible (Anderson et al 2008).

Transects were used to estimate percent cover of bare ground exposure, rock (>75 mm), litter, herbaceous standing dead, dead standing wood, live herbaceous species, live shrubs, and dominant weed. Percent cover estimates were made along two 10 m line transects. Transects were arranged perpendicular to each other and crossing at the center of the plot at the 5 m mark of each line transect. Using the point-intercept method, observations were recorded every 20 cm along each 10 m line, beginning at 10 cm and ending at 990 cm. The cover type (bare ground exposure, rock (>75 mm), litter, herbaceous standing dead, dead standing wood, live herbaceous species, live shrubs, and dominant weed) at each observation point was recorded (Tibbitts et al 2007).

Plant Biomass Measurement

Available forage was measured using a plastic coated cable hoop 2.36 meters in circumference, or 0.44 m^2. The hoop was randomly tossed into each of four quadrants (NW, NE, SE, and SW) centered over the sample point. All grass species within the hoop considered forage for cattle, sheep, and wild ungulates were clipped and weighed (+/-1g) using a Pesola scale tared to the weight of an ordinary paper bag. The measurements were then used to estimate forage amount in AUM's, pounds per acre, and kilograms per hectare (Anderson et al 2008).

Data Processing

MODIS LAI, GPP, PsnNet, and FPAR were acquired for the months of June, July and August 2007. The spatial resolution of all layers was 1km x 1 km, projected into Idaho Transverse Mercator (NAD83). FPAR was estimated over a period of 8 days by the University of Montana NTSG lab. They estimated daily APAR for the pixel by multiplying daily estimated PAR by the FPAR. The APAR values were then used to calculate daily GPP using equation 1. Eight day summations of GPP were then calculated and used in the study. The subsequent products (i.e. PsnNet and LAI) were also estimated over a period of 8 days. Hence, all MODIS products used in this study had a temporal resolution of 8 days (Heinch et al 2003).

Landscape-scale validation

Each MODIS product was independently tested for correlation with percent cover and plant biomass. Since the Big Desert study site field data were collected during the first two weeks of June 2007, MODIS products for the first two weeks of June 2007 were chosen to correlate with these data. Similarly MODIS products for the first two weeks of July 2007 were chosen for the O'Neal study site and MODIS products for the first two weeks of August 2007 were similarly chosen for the USSES study site.

Using ESRI ArcGIS, the value of the MODIS pixel at each sample site (n=347) was extracted and stored in a database table. These results were then converted to a file format usable by MS Excel. The resulting spreadsheet contained percent cover and plant biomass attributes along with the extracted LAI, GPP, PsnNet, and FPAR pixel values. The extracted data for each MODIS product was correlated against percent cover and plant biomass values across each of the three study sites (e.g., percent cover was correlated with LAI for the Big Desert). The R^2 value for the model (using exponential, linear, logarithmic, polynomial, power or moving average lines of best fit) that consistently produced the best fit between these data is reported below.

Pixel-scale Validation

While it was procedurally important to extract and analyze the MODIS values at each sample location (n=347), it was equally important to assess just those pixels that contained three or more sample locations (n= 19) to try to capture some of the variability within each pixels and thereby produce a better representative of each pixel's value. This assessment was considered important for coarse resolution imagery such as MODIS as the generalization of *in situ* field observations (using mean or median) may better reflect the characteristics of the landscape. To accomplish this, all pixels for the USSES and O'Neal study sites containing 3 or more sample points per pixel were identified (n=19). For USSES and O'Neal average number of samples per pixel were 6 and 35 respectively. When combined; overall average number of samples per pixel was 12. USSES had the least samples per pixel i.e. 3 whereas O'Neal had the maximum samples per pixel i.e. 86. (Note: the Big Desert study area was not included in this part of the study as these field samples were too broadly distributed). For the USSES study area, FPAR and PsnNet images obtained on 07-28- 2007 were used whereas FPAR and PsnNet images obtained on 06- 26-2007 were used for O'Neal study area analysis. A total of 15 pixels were included from the USSES and 4 pixels were included from the O'Neal study site. Mean and median values for both percent cover and plant biomass (kg/ha) were correlated with FPAR and PsnNet values. These specific products (FPAR and PsnNet) were chosen for pixel scale validation as FPAR is the most basic product (least processed productivity product) whereas PsnNet is the most processed product, hence it was hoped that some relationship would be revealed by these comparisons. The specific differences between these products are the PAR conversion efficiency (ε), leaf maintenance respiration factor, and fine root mass maintenance respiration factor. With this in mind, we anticipated a trend in the correlations between the least processed (FPAR) and most highly processed products (PsnNet). Further, we expected a more direct correlation of percent cover and plant biomass (kg/ha) with FPAR and PsnNet and chose linear regression for all analyses. The coefficient of correlation (R^2) was calculated for each test and reported below.

RESULTS AND DISCUSSION

Landscape-scale Validation

Second order polynomial model results are reported here as they consistently produced the highest R^2 values compared to all other models tested. The R^2 values for correlations of the MODIS products with percent cover and plant biomass for the Big Desert, USSES, and O'Neal study sites are summarized in Table 1, 2 and 3. It can be seen that all R^2 values are below 0.1 indicating very weak correlation among the MODIS products and the percent cover and forage values at the 3 study sites.

Table 1. Correlation coefficient (R^2) between *in situ* field measurements (total percent cover and plant biomass) and various MODIS productivity products (FPAR, GPP, LAI, and PsnNet) for the Big Desert study site.

	Correlation (R^2) of	
Big Desert (06/02/07)	**% Cover**	**Forage (kg/ha)**
FPAR	0.057	0.0508
GPP	0.045	0.0476
LAI	0.0482	0.073
PsnNet	0.018	0.0297
Mean R^2	*0.0421*	*0.0503*
Big Desert (06/10/07)	**% Cover**	**Forage (kg/ha)**
FPAR	0.0433	0.0746
GPP	0.0576	0.0741
LAI	0.0374	0.0607
PsnNet	0.0462	0.0744
Mean R^2	*0.0461*	*0.0710*

Table 2. Correlation coefficient (R^2) between *in situ* field measurements (total percent cover and forage biomass) and various MODIS productivity products (FPAR, GPP, LAI, and PsnNet) for the USSES study site.

	Correlation (R^2) of	
USSES (08/05/07)	**% Cover**	**Forage (kg/ha)**
FPAR	0.0095	0.0911
GPP	0.0121	0.0745
LAI	0.0163	0.0557
PsnNet	0.013	0.0314
Mean R^2	*0.0127*	*0.0632*
USSES (08/13/07)	**% Cover**	**Forage (kg/ha)**
FPAR	0.0179	0.0599
GPP	0.0208	0.0546
LAI	0.024	0.0679
PsnNet	0.0145	0.018
Mean R^2	*0.0193*	*0.0501*

Table 3. Correlation coefficient (R^2) between *in situ* field measurements (total percent cover and forage biomass) and various MODIS productivity products (FPAR, GPP, LAI, and PsnNet) for the O'Neal study site.

	Correlation (R^2) of	
O'Neal (07/04/07)	**% Cover**	**Forage (kg/ha)**
FPAR	0.014	0.0324
GPP	0.0243	0.0352
LAI	0.031	0.0165
PsnNet	0.0409	0.0092
Mean R^2	*0.0276*	*0.0233*
O'Neal (07/12/07)	**% Cover**	**Forage (kg/ha)**
FPAR	0.0287	0.0501
GPP	0.0568	0.0523
LAI	0.0384	0.0645
PsnNet	0.0154	0.0657
Mean R^2	*0.0348*	*0.0582*

Although the direct correlation between percent cover and biomass was weak ($R^2 = 0.1211$, n = 347), we assumed the quantity of biomass depended largely on percent cover. This suggests that correlations using either of these field-based productivity measures should result in highly similar (autocorrelated) results. However, since the biomass values used in this study only included grass, total percent cover should have yielded a better relationship with MODIS productivity products. The comparison of MODIS correlations with percent cover and biomass reveals the opposite. The R^2 values for biomass were typically better than the R^2 values for total percent cover (twenty comparisons out of 24 [i.e. 83% of the observations]). The field methods used to measure total percent cover and forage biomass can certainly play a role and these results suggest that the biomass estimation variable may be a more reliable estimate of overall productivity compared to total percent cover.

Correlations between MODIS products and the *in situ* field data for the Big Desert study site were consistently better than found at the other sites (mean R2 = 0.04 for percent cover and 0.06 for biomass [table 4]).

Table 4. Mean correlation coefficient (R^2) between *in situ* field measurements (total percent cover and forage biomass) and various MODIS productivity products (FPAR, GPP, LAI, and PsnNet) for the three study sites.

	Correlation (R^2) of	
	% Cover	**Forage (kg/ha)**
Big Desert (06/02/07)	**0.0421**	**0.0503**
Big Desert (06/10/07)	**0.0461**	**0.0710**
O'Neal (07/04/07)	0.0276	0.0233
O'Neal (07/12/07)	0.0348	0.0582
USSES (08/05/07)	0.0127	0.0632
USSES (08/13/07)	0.0193	0.0501

This is of particular interest, because percent cover at the Big Desert was estimated in ocular fashion using fairly broad classes (approximately 10% cover intervals) compared to point-intercept transect data used at the other two sites.

Pixel-sc ale Validation

The results of validation for those pixels containing 3 or more sample points indicate that percent cover and plant biomass share a weak correlation with FPAR and PsnNet (Table 5). The correlation improves slightly (from 0.0094 to 0.1129 for percent cover and from 0.0549 to 0.1029 for biomass) suggesting a dependence on the level of processing (FPAR being the most basic to PsnNet the most processed) with the more highly processed product being having a slightly higher correlation field data.

Table 5. Pixel scale correlation coefficients (R^2) between *in situ* field measurements (total percent cover and forage biomass) and two MODIS productivity products (FPAR and PsnNet).

	Correlation (R^2) of	
	% Cover (Mean)	**Forage kg/ha (Mean)**
FPAR	0.0094	0.0549
PsnNet	0.1129	0.1029

Past studies suggest that MODIS products will not correlate well at the pixel scale, whereas multi-pixel patch level comparisons have demonstrated improved correlation between field measurements and satellite derived products (Wang et al 2004). The present study suggests that the results of validation for pixels containing 3 or more sample points are slightly better than the results for validation using all pixels across the study's landscape thereby supporting the findings of Wang et al.

The results in Table 5 are combined results for the two sites i.e. O'Neal and USSES. We also examined the individual correlations for the same. The R^2 ranges from 0.00 (for O'Neal - PsnNet and percent cover relationship) to 0.19 (for USSES – FPAR and forage relationship). This implies that none of the study sites possesses a strong correlation with MODIS products.

Assessment of Error and Bias

Heterogeneity in the native vegetation contributes to the variation in the R^2 values especially for LAI values. An effect of foliage clustering and discontinuities is well documented and can significantly affect LAI values (Shabanov et al 2003).

Other spatiotemporal factors may also have contributed to the weak relationship seen in this study. We chose MODIS products acquired on 07- 28- 2007 and 06- 26-2007 for the USSES and O'Neal respectively for pixel scale validation. Although these products should closely represent the field scenario, from the results it is clear that the MODIS products and the field scenario vary from each other. The field attributes (percent cover and forage biomass) for the points in a pixel can be entirely different. Norton and others have reported that there can be significant variability between the field measurements of even two samples made in close proximity (+/- 5 m; (Norton 2008). In this study, we dealt with two vegetation characterization estimates (total percent cover and biomass) and attempted to correlate these over areas that were 1000m in size (1 km MODIS pixels). Not surprisingly then, significant variability was encountered. To better characterize the variability within each pixel, many more sampling points are required with a better distribution d within each pixel.

CONCLUSIONS

Biomass measurements correlated better with MODIS products than did percent cover estimates Forage biomass is defined as all grass species except invasive weeds (Gregory et al 2005) while percent cover included everything except bare ground, litter and rocks. This suggests that non-grass species may have interacted differently with photosynthetically active radiation there by resulting in the poor correlations of percent cover to the MODIS products.

No pattern can be seen for R^2 values for any of the three sites. However distribution of the data points was different for all three sites. The Big Desert data points were well distributed across the study area landscape and exhibit a better range of values for the MODIS products as compared to USSES and O'Neal sites (Figures 2-4).

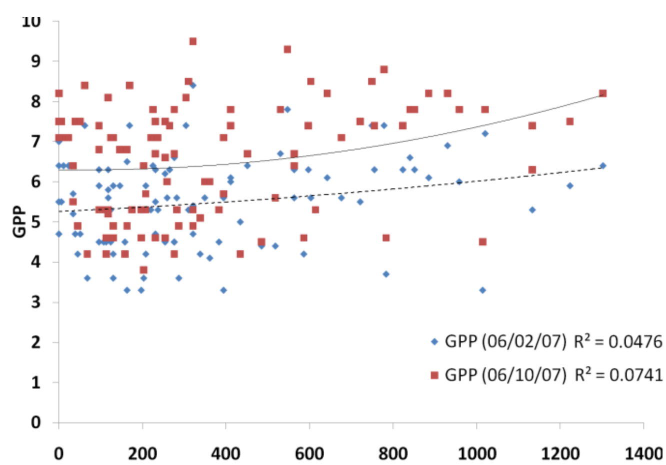

Figure 2. GPP vs. Forage for the Big Desert study area

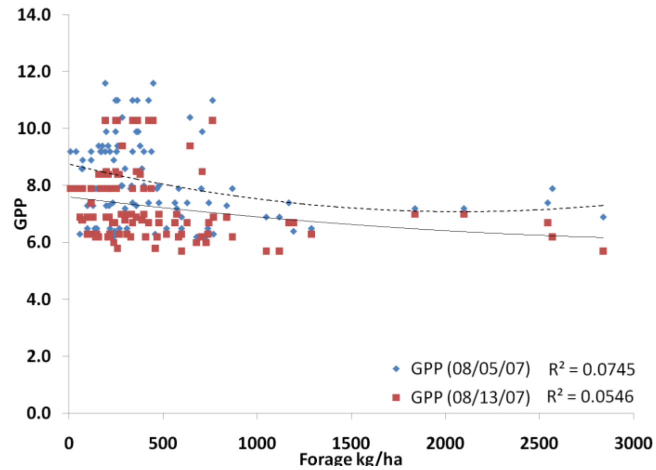

Figure 3. GPP vs. Forage for the USSES study area

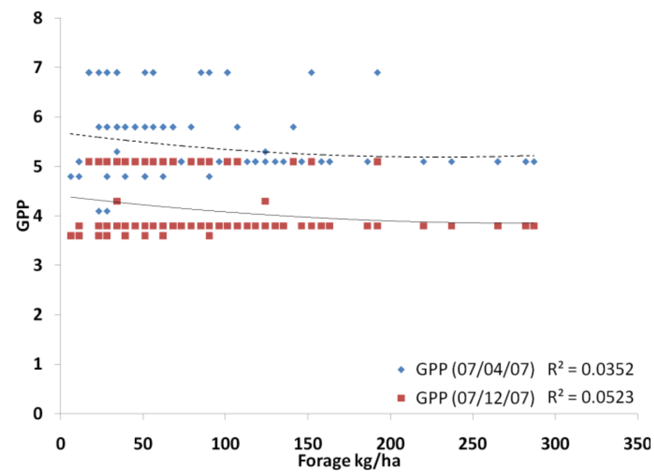

Figure 4. GPP vs. Forage biomass for the O'Neal study area

This study underlines the need to understand potential effect of the spatial distribution of data points with a study area. The Big Desert study area covers over 1000 km^2 which means several MODIS pixels are available for analysis. But the USSES and O'Neal study areas are in the order of only tens of km^2 in size and contain only a few MODIS pixels each.

The importance of this fact is also underlined by revisiting the R^2 values for the Big Desert study site. These values were better --compared to those for USSES and O'Neal—perhaps only because of the better spatial distribution of data points over the study area relative to the size and extent of the MODIS pixels. Pixel-scale validation did not improve the correlation between the MODIS products and field attributes. Spatiotemporal factors and/or the level of MODIS product processing are likely the reason for such poor results.

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Multi-sensor Analysis of Vegetation Indices in a Semiarid Environment

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ABSTRACT

Multi-sensor comparisons are sometimes used due to limited image availability and temporal coverage by a single sensor. However, multi-sensor comparability is not well documented. Factors affecting direct comparability such as atmospheric conditions, landscape heterogeneity, landscape changes, and sensor characteristics are difficult to quantify. This study compared several vegetation indices (VIs) from multi-sensor data to determine if VIs are comparable across scales and sensors. Within-sensor comparisons demonstrate that VIs are consistent across spatial resolutions indicating a direct multi-scale comparability. However, among-sensor comparisons indicate that VIs calculated from different sensors are not comparable with one another regardless of spatial resolution. Sensor-specific characteristics appear to offer the best explanation for the observed results.

KEYWORDS: satellite imagery, NDVI, scale

INTRODUCTION

Drylands cover 41% of the earth's land surface and are home to one-third of the world population (IUCN, 2007). Vegetation productivity of semi-arid ecosystems is limited by inter-annual variability in precipitation (Holmgren et al., 2006) and is relatively vulnerable to human and natural disturbances. To monitor these vast areas, satellite remote sensing is commonly used. However, remote sensing of semi-arid landscapes is challenging because of the difficulty in detecting low levels of biomass and sparse vegetation (Leprieur et al., 2000) amidst relatively high proportions of exposed soil. The presence of litter and other non-photosynthetic vegetation, which are also common in semi-arid environments, further complicates the issue (van Leeuwen and Huete, 1996). Numerous studies have characterized vegetation in arid and semi-arid environments using vegetation indices (VIs) with spectral data from a single sensor (Elmore et al., 2000; Hunt and Miyake, 2006; Marsett et al., 2006; McGwire et al., 2000; Washington-Allen et al., 2006; Xiao and Moody, 2005). However, data from multiple sensors are sometimes used together (García-Gigorro and Saura, 2005) due to limited data availability from a single sensor, varying temporal coverage by different sensors (e.g. MODIS and AVHRR), and use of high spatial resolution products to validate or calibrate coarse spatial resolution images and models (Hu and Islam, 1997; Leprieur et al., 2000).

Various factors such as the atmospheric conditions during acquisition, landscape heterogeneity, landscape changes, and sensor characteristics influence direct comparability (i.e., scaling) of VIs between different sensors. Their effects on VIs, however, are not well understood and are difficult to quantify. For instance, atmospheric conditions are not consistent over space and time and are difficult to fully correct due to a lack of precise atmospheric parameters at the time of acquisition across the entire field of view, although models such as Cos(t) (Chavez, 1996) are often used to reduce atmospheric effects. Furthermore, sensor characteristics vary between platforms and sensors. Geometric characteristics, such as viewing angle, field of view, and sun elevation may be different in addition to the intrinsic characteristics of the sensor (scanning system construction, band width, band center, signal-to-noise ratio)(Lillesand and Kiefer 2000). The impact of these factors can be reduced by using sensors with similar characteristics (e.g. Landsat MSS and Landsat TM). However, due to limited choices of imagery, images from multiple sensors are commonly used (Buheaosier et al., 2003; Teillet et al., 1997).

The comparison of imagery from multiple sensors typically implies the use of multi-date imagery. As a result, the temporal difference will result in changes on the ground due to plant phenology, weather conditions, and human perturbations. These differences are almost impossible to correct for and minimizing the differences in acquisition times between imagery is the only viable solution.

Several studies have attempted to analyze the effects of scale on vegetation indices directly (Aman et al., 1992; Buheaosier et al., 2003; Goodin and Henebry, 2002; Hu and Islam, 1997; Jiang et al., 2006; Tarnavsky et al., 2008; Teillet et al., 1997; Wood and Lakshmi, 1993) and indirectly using fragmentation indices (García-Gigorro and Saura, 2005; Saura, 2004) or leaf area index estimations (Chen, 1999; Sprintsin et al., 2007). However, these studies focused mostly on NDVI in forested areas with a spatial resolution > 30 meters. To our knowledge, no study has attempted to exclusively examine the comparability of several VIs from multiple sensors in semi-arid environments. The objective of this study was to examine the comparability of multi-sensor imagery to characterize a semi-arid environment by: 1) comparing VI values at the same point locations using increasing pixel sizes *within* the same sensor, and 2) comparing VI values at the same point locations using increasing pixel sizes *across* different sensors.

METHODS

Study area

The study area is located in sagebrush-steppe rangelands of southeastern Idaho (Fig. 1) in the vicinity of the O'Neal Ecological Reserve (property of Idaho State University). The area covers 64 km^2 and is located along the Portneuf River approximately 25 km southeast of Pocatello, Idaho, USA. It contains riparian areas and cultivated crop fields as well as typical sagebrush steppe upland areas located on lava benches. The area receives an average of 0.41 m of precipitation annually (primarily during the winter) and the annual mean temperature is 7.8 °C with a mean of 18.9 °C in the summer and 3.4 °C in the winter (based upon monthly averages) (WRCC, 2007). The terrain is relatively flat with an average elevation of 1400 m. The dominant plant species in the sagebrush steppe is big sagebrush (*Artemisia tridentata*) with various native and non-native grasses such as indian rice grass (*Oryzopsis hymenoides*), needle-and-thread (*Stipa comata*), and cheatgrass (*Bromus tectorum*). The cultivated areas are dominated by wheat and forage such as alfalfa (*Medicago sativa*).

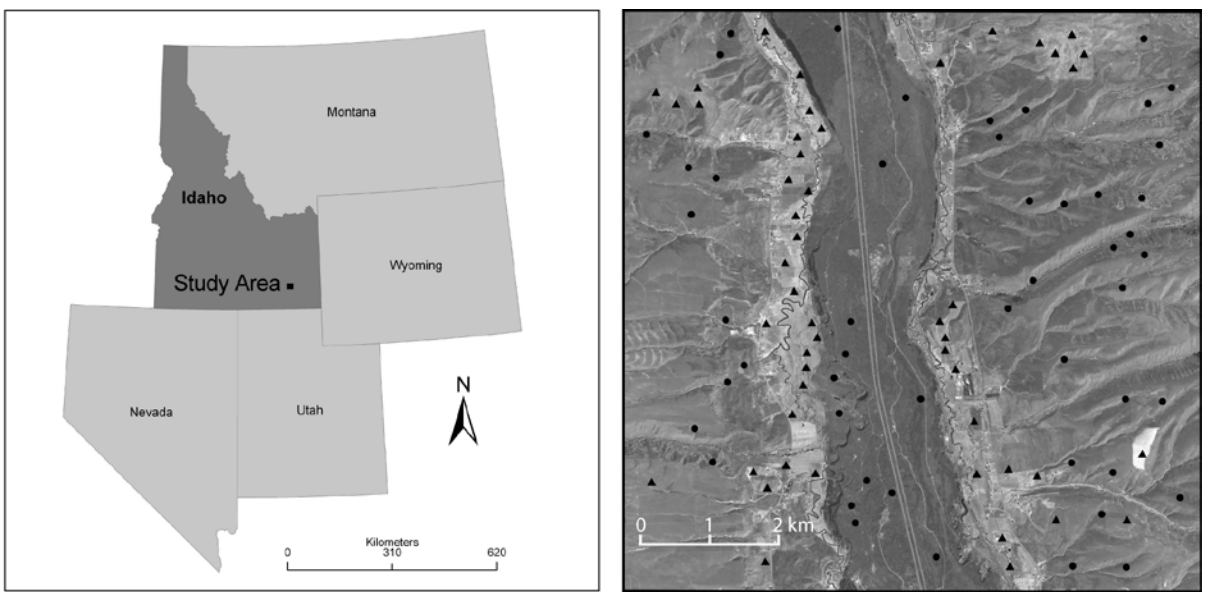

Figure 1. Study area and sampling locations used to calculate vegetation indices. Sampling stratification is shown for shrub/grassland cover type (dots) and cultivated crops/hay land cover type (triangles).

Satellite Imagery

Imagery from four commonly used satellite platforms were selected: QuickBird, SPOT5 HRG (Haute Résolution Géométrique), Landsat5 TM (Thematic Mapper), and MODIS. We selected June 26th 2006 as the target date and imagery from different sensors were acquired to match this date as closely as possible (Table 1). All QuickBird, SPOT5 HRG, and Landsat5 TM images were atmospherically corrected and converted to reflectance using the Cos(t) model (Chavez, 1996) to reduce variability of vegetation indices due to the heterogeneity in the radiometric processing of data (Guyot and Gu, 1994). MODIS imagery was received in reflectance format ("MOD09GQ" data).

Table 1. Description of imagery used in this study

Sensor Name	Acronym Definition	Acquisition Date	Spatial Resolution (m)
QuickBird	-	June-28-2006	2.5
SPOT5 HRG	Satellite Pour l'Observation de la Terre 5 Haute Résolution Géométrique	June-25-2006	10
Landsat5 TM	Thematic Mapper	June-13-2006	28.5
MODIS	Moderate-resolution Imaging Spectroradiometer	June-13-2006 June-25-2006 June-26-2006 June-28-2006	250

All imagery was projected into Idaho Transverse Mercator NAD83 projection and datum using nearest neighbor resampling. Georectification of each image was assessed using 1-m resolution orthorectified aerial images acquired in 2004 as part of the National Agricultural Imagery Program to ensure spatial co-registration consistency between scenes. The assessment indicated that the georectification of MODIS and QuickBird imagery was satisfactory and no additional georectification was performed. However, an additional georectification was performed on both SPOT5 HRG and Landsat5 TM images using ground control points selected from the orthorectified aerial images. The resulting root mean squared errors (RMSE) were 3.80 and 11.27 m respectively.

Image processing

While some VIs that include the mid-infrared band are used in semi-arid environments (Marsett et al., 2006) this band is not available for every sensor (e.g., QuickBird). Therefore, the VIs compared in this study were limited to those derived from the red/infrared bands (Table 2). The spectral and spatial characteristics of the red and infrared bands of the sensors used in this study are presented in Fig. 2 to illustrate band width and band centers.

Table 2. Description of vegetation indices selected in this study for spatial scale comparison

Name	Full name	Formula	Reference
NDVI	Normalized Difference Vegetation Index	$\frac{NIR - R}{NIR + R}$	Rouse et al. (1974)
RVI	Simple Ratio Vegetation Index	$\frac{R}{NIR}$	Richardson and Wiegand (1977)
NRVI	Normalized Ratio Vegetation Index	$\frac{RVI - 1}{RVI + 1}$	Baret and Guyot (1991)
SAVI	Soil-Adjusted Vegetation Index	$\frac{NIR - R}{NIR + R + L} \times (1 + L)$	Huete (1988)
$MSAVI_2$	Modified Soil Vegetation Index	$\frac{2NIR + 1 - \sqrt{(2NIR + 1)^2 - 8(NIR - R)}}{2}$	Qi et al. (1994)

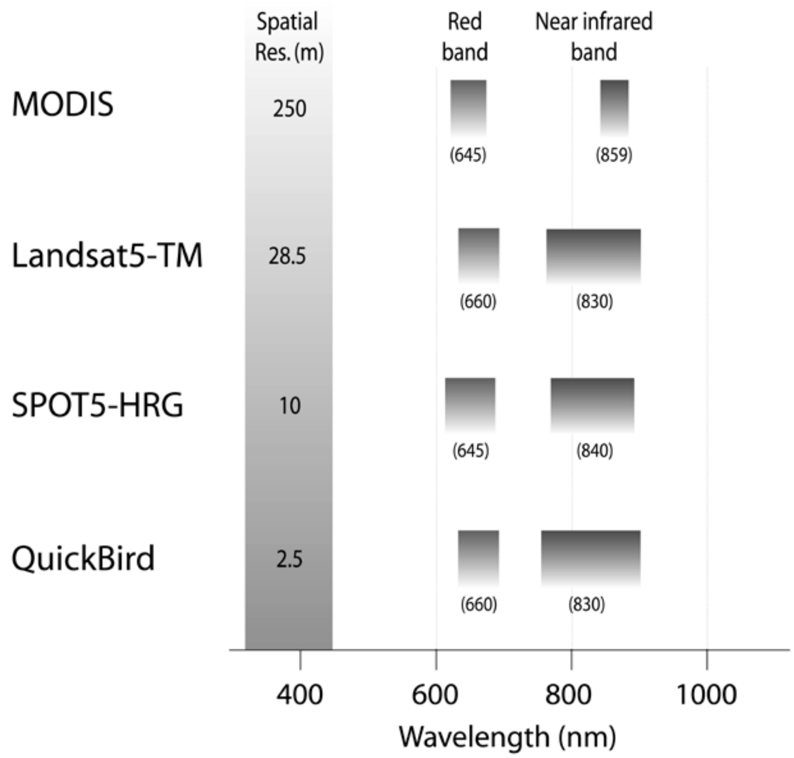

Figure 2. Spatial and spectral characteristics of red and near infrared bands of the sensors used in this study. Wavelengths of band centers are shown in brackets.

VIs were calculated at the native resolution of each sensor (Table 1). These VI images were then re-sampled using a common pixel aggregation function (average) to correspond to the coarser spatial resolutions of the other sensors used in this study. We consistently used only one resampling algorithm, because our goal was not to explore the effect of different resampling algorithms. However, other aggregation functions are available and can produce different results (García-Gigorro and Saura 2005).

Because the study area is heterogeneous and covers different land cover types, the images were stratified to reduce potential variability in VI values due to landscape heterogeneity and thereby better compare the effects of scale. Two land cover types were selected using an independent classification of the area from the National Land Cover Database (NLCD) of 2001 (Homer et al., 2004) and the following criteria: 1) each land cover type was large enough to select 50 independent sample points at the coarsest spatial resolution used (250 m) and, 2) the land cover type was composed of patches larger than the coarsest spatial resolution used (250 m). The selected land cover types were shrub/grassland and cultivated crops/hay. Analyses were performed in these strata using separate masks.

Statistical Analysis

All statistical analysis used samples from 100 randomly-selected point locations. Samples from the two land cover types (50 point locations each) were examined separately in all analyses. One-way analysis of variance (ANOVA) with all pair-wise post-hoc comparisons were used to compare all possible combinations of resolutions and sensors.

First, the VIs were examined across different resolutions within the same sensor to compare VI values at the native resolution to VI values at various aggregated resolutions. In this analysis, NDVI, NRVI, SAVI and $MSAVI_2$ were separately compared across various resolutions. For QuickBird imagery, native 2.5 m, 10 m, 28.5 m, and 250 m resolutions were used, whereas three resolutions were used for SPOT5 HRG imagery (native 10 m, 28.5 m, and 250 m), and two resolutions of Landsat5 TM imagery were used (native 28.5 m and 250 m). The increasing sizes of resolution were the predictor variable and the estimated VI values were the response variable.

Secondly, each VI was compared among different sensors to determine scalability between platforms. In this analysis, NDVI, NRVI, SAVI, and $MSAVI_2$ were separately compared among QuickBird, SPOT5 HRG, Landsat5 TM, and MODIS sensors using their native resolutions as well as their aggregated resolutions to determine if VI values from different sensors were significantly different from each other when using native versus aggregated resolutions. For example, NDVI values from 2.5-m-resolution QuickBird imagery were compared to NDVI values from 10-m-resolution SPOT5 HRG, 28.5-m-resolution Landsat, and 250-m-resolution MODIS images. Similarly, NDVI values from aggregated 10-m-resolution QuickBird imagery were compared to 10-m-resolution SPOT5 HRG imagery, values from aggregated 28.5-m-resolution QuickBird imagery were compared to 28.5-m-resolution Landsat5 TM imagery, and values from aggregated 250-m-resolution QuickBird imagery were compared to 250-m-resolution MODIS values. In this way, all combinations of sensors and resolutions were tested. The native or aggregated resolutions from the different sensors were the predictor variable and the estimated VI values were the response variable.

Finally, complementary analyses were performed to study the effect of image acquisition date on vegetation index values. MODIS images from June 13th, June 25th, and June 28th were acquired to correspond to the same acquisition dates of the Landsat5 TM, SPOT5 HRG, and QuickBird images used in this study, respectively. NDVI and $MSAVI_2$ values from the same point locations used in the analyses above were compared for each date-synchronous pair of images: MODIS from June 13th and Landsat5 TM, MODIS from June 25th and SPOT5 HRG, and MODIS from June 28th and QuickBird imagery. Aggregated 250 m pixels from the finer resolution imagery were used to compare at native MODIS resolution.

RESULTS

Within-sensor comparisons

ANOVA test results indicate that different resolutions of QuickBird, SPOT5 HRG, and Landsat5 TM were not significant as predictor variables ($P > 0.05$) and no statistically significant differences were found in NDVI, NRVI, SAVI, and $MSAVI_2$ values among the four different resolutions of QuickBird, three resolutions of SPOT5 HRG, and two resolutions of Landsat5 TM imagery (Fig. 3 (a, b, c, d, e, and f)) for either land cover type.

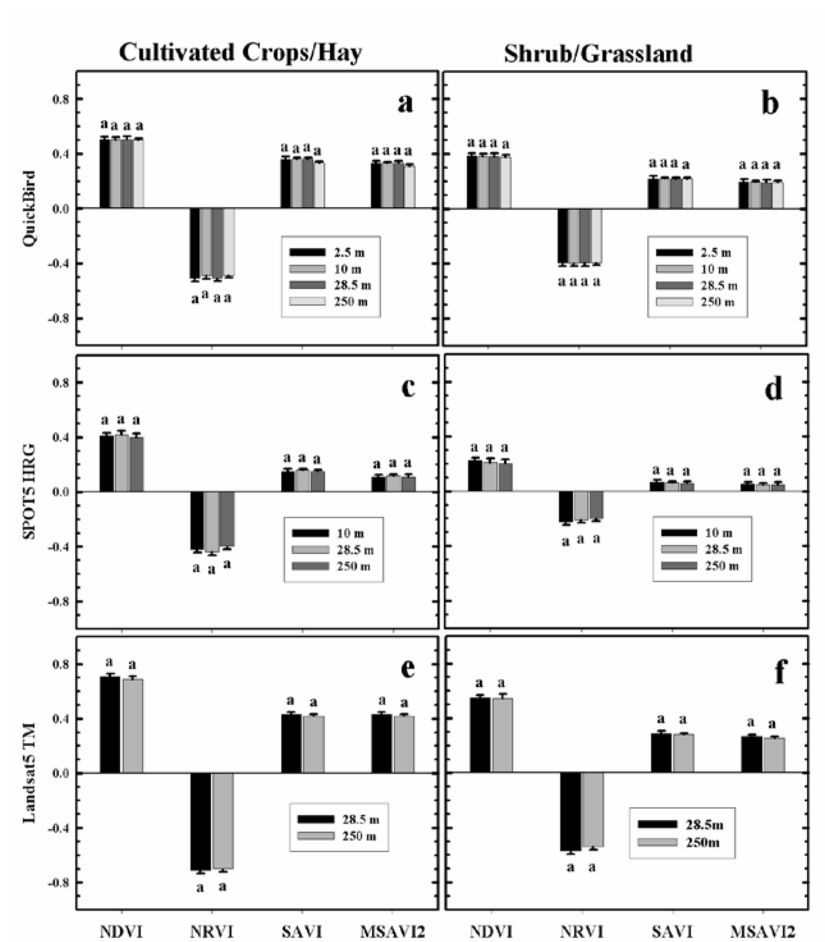

Figure 3. Vegetation index comparisons within sensors. The estimated mean (±SE) value of each vegetation index is separately compared among four different scales for QuickBird imagery (a and b), three different scales for SPOT5 HRG imagery (c and d), and two different scales for Landsat5 TM (e and f). No statistically significant differences were found in any of the comparisons among different scales of each vegetation index.

Among-sensor comparisons

The native and aggregated resolutions from different sensors were significant as predictor variables (P <0.000) and post-hoc comparisons indicated many significant differences (Fig. 4).

- NDVI values from the cultivated crop/hay cover type were significantly different in all pair-wise comparisons (P <0.000), except the comparison between 2.5-m-resolution QuickBird and 250-m-MODIS imagery (P =0.566) (Fig. 4g). NDVI values from the shrub/grassland cover type were also significantly different in all pair-wise comparisons (P <0.000), except the comparison between 28.5-m-resolution Landsat5 TM and 250 m MODIS imagery (*p* =1.000) (Fig. 4h).
- NRVI values from the cultivated crop/hay cover type were significantly different in all pair-wise comparisons (P <0.000), except the comparison between 2.5-m-resolution QuickBird and 250-m–resolution MODIS imagery (P =0.566) (Fig. 4g). NRVI values from the shrub/grassland cover type were also significantly different in all pair-wise comparisons (P <0.000), save for the comparison between 28.5-m-resolution Landsat5 TM and 250-m-resolution MODIS imagery (P =1.000) (Fig. 4h).
- SAVI values from the cultivated crop/hay cover type were significantly different among all resolutions of QuickBird, SPOT5 HRG, and Landsat5 TM images (P <0.000), but no difference was found between

2.5-m-resolution QuickBird and 250-m-resolution MODIS imagery (P <0.064) and between 28.5-m and 250-m-resolution Landsat5 TM images and 250-m-resolution MODIS imagery (P =1.00 and 1.00, respectively) (Fig. 4g). SAVI values from the shrub/grassland cover type were significantly different in all pair-wise comparisons (P <0.000), except the comparison between 28.5–m-resolution Landsat5 TM and 250-m-resolution MODIS imagery (P <0.115) (Fig. 4h).

- $MSAVI_2$ values from the cultivated crop/hay cover type were significantly different in all pair-wise comparisons (P <0.000), except the comparison between 28.5-m- and 250-m-resolution Landsat5 TM images and 250-m-resolution MODIS imagery (P =1.00 and 1.00, respectively) (Fig. 4g). $MSAVI_2$ values from the shrub/grassland cover type were also significantly different in all pair-wise comparisons, except the comparison between 28.5-m-resolution Landsat5 TM and 250-m-resolution MODIS imagery (P =0.06) (Fig. 4h).

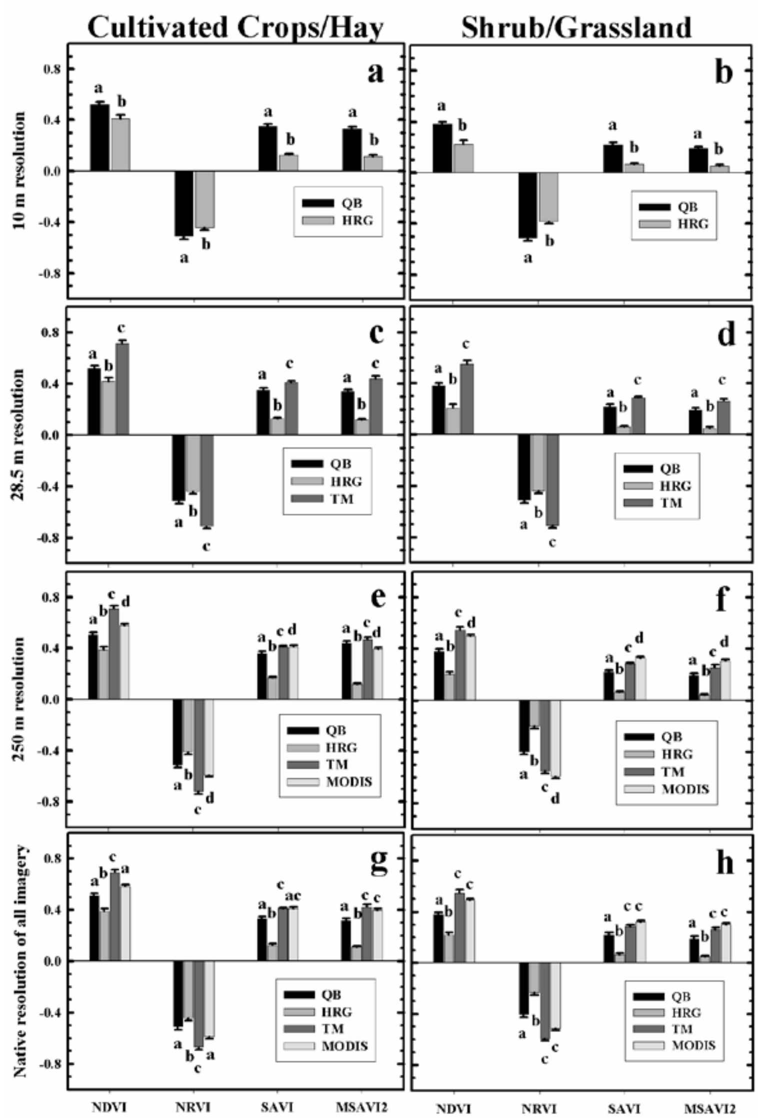

Figure 4. Vegetation index comparisons across sensors. The estimated mean (+SE) value of each vegetation index is separately compared across the four different sensors at aggregated resolutions of 10 m (and b), 28.5 m (c and d), and 250 m (e and f), as well as their native resolutions (g and h). Many statistically significant differences were found in the estimated mean values of the same vegetation index between different sensors.

Date-synchronous comparisons

The comparison between $MSAVI_2$ and NDVI values between data-synchronous pairs of imagery indicated many significant differences (Fig. 5). Comparisons between the June 13th MODIS and Landsat5 TM imagery indicated significant differences for both VIs and cover types ($P < 0.05$). The same results were observed in the comparison between the June 28th MODIS and QuickBird imagery ($P < 0.05$). Significant differences were also found when the June 25th MODIS and SPOT5 HRG imagery were compared ($P < 0.05$), except the NDVI comparison in the shrub/grassland cover type ($P=0.074$) (Fig. 5d) and $MSAVI_2$ comparison from the cultivated crop/hay cover type ($P=0.06$) (Fig. 5a).

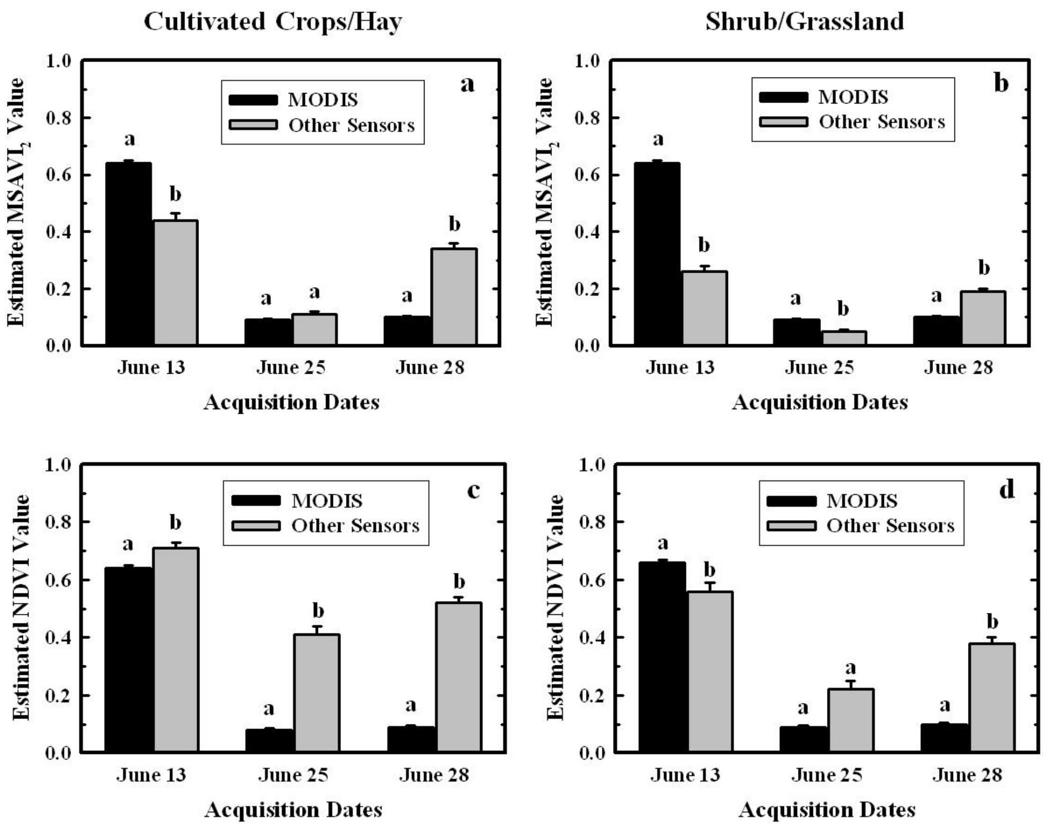

Figure 5. Pair-wise comparisons of MODIS $MSAVI_2$ and NDVI values with $MSAVI_2$ and NDVI values from Landsat5 TM, SPOT5 HRG, and QuickBird images acquired on June 13th, June 25th, and June 28th 2006, respectively. Most pairs of images acquired on the same day had significantly different (indicated by letters) $MSAVI_2$ and NDVI values.

DISCUSSION

Effects of landscape heterogeneity

Results from the within-sensor comparisons indicate no significant effect of scale on VI values. These results suggest that VIs derived from the same sensor are comparable when pixels are aggregated to coarser resolutions. The relatively homogeneous spatial pattern found in the crops/hay cover type can explain the scalability of VIs for this land cover type. The range of spatial resolution used (i.e., 2.5 - 250 m) was smaller than the size of a typical crop field and consequently aggregated pixels at each point were likely located within the same crop field. This ensured relatively stable radiometric conditions resulting in similar VI values. Hu and Islam (1997) identified land surface homogeneity as a condition under which algorithms such as VIs can be “up-scaled” or “down-scaled” without incurring significant differences. In addition, Teillet et al. (1997) found similar results over forested areas with constant NDVI values at different spatial resolutions for the same sensor, except when it reached a scale on the order of the size of land cover patches. In that study, one threshold was approximately 260 m which corresponded to the size of the forest stands evaluated in that study.

In the case of the shrub/grassland cover type, the scalability results were unexpected. Pixels in this environment are relatively heterogeneous with a mix of bare ground, shrubs, and shadow in various proportions and sizes. Significant differences in VIs associated with the change of spatial resolution were expected as shown by Jiang et al. (2006) who found strong spatial scale dependencies of NDVI over heterogeneous surfaces. However, the Jiang et al. study (using simulated data) pointed out that NDVI can be scale invariant over heterogeneous surfaces when the brightness (sum of red and NIR reflectance) of vegetation is equal to that of soil background. This might partially explain our results. Another study from our study area presents spectral signatures of common land cover elements and describes a similar pattern in brightness between bare ground and big sagebrush plants, the dominant vegetation species of the area (Weber et al., 2008).

Most of the literature regarding scale effects on VIs has focused on NDVI. Our study showed that NRVI, SAVI, and $MSAVI_2$ follow the same patterns as NDVI in terms of within-sensor scalability. Our results further suggest that VI layers can be aggregated to fit other GIS layers (e.g., for spatial analysis purposes) in semi-arid environments.

Effects of sensor characteristics

Many statistically significant differences were found when VIs were compared using native and aggregated resolutions across QuickBird, SPOT5 HRG, Landsat5 TM, and MODIS sensors. QuickBird, SPOT5 HRG, Landsat5 TM, and MODIS images did not produce the same VI values at the same locations, except for only a few cases. Further, the finer resolution imagery (QuickBird, SPOT5 HRG, and Landsat5 TM) did not produce the same or even similar VI values, when aggregated to match the pixel sizes of the coarser resolution imagery.

This lack of agreement may be due to sensor-specific characteristics such as systematic, radiometric, and spectral differences as well as differences in scene-specific characteristics such as variations in the atmospheric conditions on the specific acquisition date. Teillet et al. (1997) found similar results over forested areas and noted that even after radiometric calibration and atmospheric correction, NDVI values calculated from medium and low resolution sensors were not comparable. Buheaosier et al. (2003) also found differences in NDVI calculated from sensors with different resolutions over several land cover types. However, they did not test for statistical significance of these differences. The results presented here extend the observations to semi-arid environments for several VIs with the observed differences expressed statistically.

Another sensor-specific difference is the variation in bandwidths and bandcenters for the red and near infrared bands of each sensor. Teillet et al. (1997) conducted a detailed study of the dependence of VIs on the location and width of red and infrared bands over forested areas. They found that an increase in the bandwidth of red and infrared bands leads to a decrease in NDVI values and is mostly influenced by the width of the red band. However, our results don't follow this trend. They indicate that VI values for MODIS (i.e., narrow bands) are not systematically higher than values for the other sensors (i.e., those with larger bandwidths) over the two land cover types examined. Moreover, when comparing results between Landsat5 TM and QuickBird which have identical red and near infrared bandwidth characteristics, we found a significant difference for all VIs calculated over both land cover types. We also found no significant difference between VIs calculated from Landsat5 TM and MODIS over the shrub-grassland cover type despite the fact that these sensors have dissimilar band characteristics. The same pattern was also observed between VIs calculated from QuickBird and MODIS (except $MSAVI_2$) over cultivated crop/hay cover type. These results seem to indicate that even if bandwidth and land cover have an influence on VI values, other factors evidently play a larger role in explaining the differences in VI values calculated from these different sensors.

Effects of landscape changes
Because of limited availability of imagery for the study area on the targeted date (June 26th 2006), imagery was acquired on slightly different dates assuming a minimal change of land characteristics would be observed over this short period of time (15 days). This same assumption is regularly made when using multi-sensor imagery or image mosaics for a target date with various methods of radiometric normalization used to minimize reflectance variations due to factors other than land surface change (Théau and Duguay, 2004). When statistically significant differences were found in VI values among the different sensors used in this study, we then sought to determine if these differences were simply due to the differences in image acquisition dates alone. If this were the case, comparisons between date-synchronous imagery would result in no significant difference between VIs. However, since there are known differences between the sensors, some difference in VIs was expected. Under this scenario, date-synchronous VI comparisons were expected to be more similar than the previous among-sensor VI comparisons which would then suggest a contributory relationship in the "difference budget" described in this paper. An examination of Z-scores from each comparison reveals consistently higher Z-scores for date-synchronous VI comparisons ($\underline{x}$ Z-score = -5.40) relative to the Z-scores from the among sensor comparisons ($\underline{x}$ Z-score = -4.95). This confirms that differences observed are primarily attributable to sensor-specific differences and incompatibilities.

The date-synchronous comparison results indicate statistically significant differences in almost all comparisons between daily MODIS NDVI and $MSAVI_2$ values and the same index values from the other sensors on synchronous dates. This indicates that even when images are acquired on the same day, there are sensor-specific differences affecting VI values. This indicates that direct comparison across sensors is not advisable. Furthermore, this implies that any inferences made using VIs from one sensor are limited.

CONCLUSIONS

The goal of this study was to assess the effect of scale on several VIs in a semi-arid environment by comparing values from the same point locations and increasing pixel sizes within the same sensors, and across different sensors. Results suggest that multi-scale comparability is applicable when aggregating pixels from the same sensor only. While the need to do this is limited, possible applications are the use of VI layers that have been aggregated to facilitate related spatial analyses with other GIS data of coarse resolution, or to complete a time series from different sensors. In contrast, multi-scale comparisons are not recommended when using different sensors. Our results also showed that the reason for these differences is primarily sensor-driven. Further research should focus on the effect of atmospheric correction methods and the effect of various aggregation methods on VI comparability as well as on the temporal variability of VIs in semi-arid environments.

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Investigation of Potential Bare Ground Modeling Techniques using Multispectal Satellite Imagery

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ABSTRACT
Bare ground exposure is an important indicator of rangeland health in semi-arid ecosystems. As such, numerous studies have attempted to detect bare ground exposure using a variety of remote sensing platforms and image processing techniques with varying levels of success. This paper describes a study that investigates the potential of various techniques, indices, and algorithms (NDVI, Angle indices, SMA, and SAM) to accurately detect bare ground exposure within semi-arid rangelands of southeastern Idaho. Results indicate that while each technique may function well where bare ground is common ($\geq$50%), none of the techniques tested appear suitable in areas where bare ground exposure rarely exceeds 35% save for the Angle at near infrared (ANIR index which may be able to detect bare ground with as little as 10% exposure.

KEYWORDS: GIS, remote sensing, bare ground exposure

INTRODUCTION

The degree of bare ground exposure has a major influence on rangeland ecological function (Whitford et al. 1998, Pyke et al. 2002, O'Brien et al. 2003, Hunt et al. 2003, Booth and Tueller 2003) and when determining rangeland health, bare ground exposure is frequently a primary indicator. In a joint collaboration between the USDI-BLM, USGS, USDA-NRCS, and USDA-ARS, 17 indicators of rangeland health were identified (Pellant 1996, Pyke et al 2002) and a subsequent USDA-ARS study (O'Brien et al. 2003) noted that 11 of the 17 indicators and a majority of indicators used by others (Williams and Kepner 2002) dealt with bare ground exposure. The degree of bare ground exposure affects the ecological attributes of soil/site stability, hydrological function, and biotic integrity (Savory 1999, Booth and Tueller 2003) and has been linked with both decreased vegetation production and biodiversity (Daubenmire 1959), increased soil erosion (Morgan 1986, Okin and Reheis 2001), and increased water run-off (Kincaid and Williams 1966, Branson and Shown 1970). Furthermore, bare ground contributes to increased amounts of particulate matter suspended in the air, through dust storms, that can consist of herbicides, pesticides, and large particulates that have detrimental health effects on humans and the environment (DeFries and Townshend 1994, Griffin et al. 2001, Okin and Reheis 2001). Since the degree of bare ground exposure is such an important indicator or rangeland health, accurate bare ground modeling provides important data to objectively assess rangelands (Whitford et al. 1998, O'Brien et al. 2000, Booth and Tueller 2003, Hunt et al. 2003) and improve the management and stewardship of these important ecosystems.

Remote sensing provides an opportunity to monitor rangelands, and specifically bare NAground exposure, at landscape scales and continuous extents with multi-temporal capabilities (Booth and Tueller 2003). Although previous studies recognize the importance of bare ground detection and modeling--and acknowledge the need for bare ground monitoring--there are a lack of studies focusing solely on bare ground detection thresholds, limitations, and reliability using remote sensing (Booth and Tueller 2003, Palmer and Fortescue 2003, Washington-Allen et al. 2006, Gokhale and Weber 2006). One difficulty in remote sensing of rangelands is the frequency of spectral mixing present within each pixel (Weber 2006).

This study investigates the suitability and limitations of bare ground detection with multispectral remote sensing data. The hypothesis of this study is that bare ground's unique spectral signal in the visible to shortwave infrared portions of the electromagnetic spectrum coupled with Spectral Mixture Analysis (SMA) and Spectral Angle Mapper (SAM) can be used to accurately discriminate and quantify bare ground exposure where bare ground is relatively rare (< 50% exposure). This hypothesis is tested through development of SMA and SAM techniques to discriminate bare ground using Satellite Pour l'Observation de la Terre 5 (SPOT 5) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) multispectral remote sensing data and various accuracy assessment techniques.

METHODS

Study Area

The O'Neal Ecological Reserve, is located in sagebrush-steppe rangelands of southeastern Idaho, and is approximately 30 km south of Pocatello (Figure 1). This 50 ha site, located along the Portneuf River, contains sagebrush-steppe upland areas upon lava benches. Adjacent to the O'Neal Ecological Reserve is a USDI BLM grazing allotment called the Rocks. The soils within the study area are a McCarey-McCarey Variant complex that is shallow and well drained. The O'Neal study area averages <0.38 m of precipitation annually with the majority falling as winter snow. The O'Neal study area is relatively flat with little relief and has an elevation of approximately 1400 m (1401-1430 m). The dominant plant species is Mountain Big Sagebrush (*Artemesia tridentata*) with various native and non-native grasses including bluebunch wheatgrass (*Pseudoroegneria spicata)*, Indian rice grass (*Oryzopsis hymenoides*), and Needle-and-Thread (*Stipa comata*).

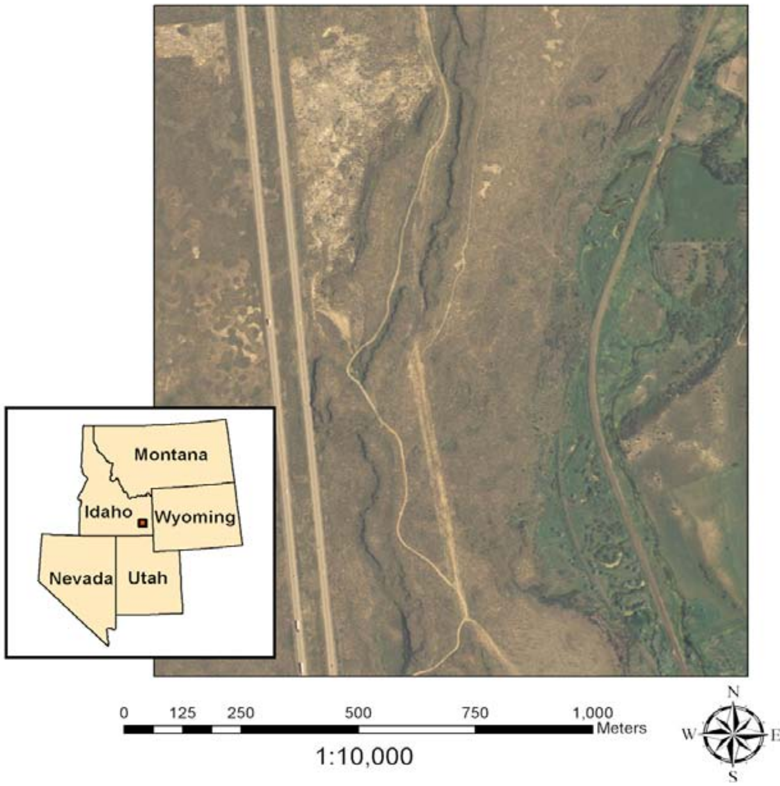

Figure 1. Location and general characteristics of the O'Neal Ecological Reserve study site.

Field Data Collection

Sample points (*n*=150) were randomly generated using Hawth's tools in ESRI's ArcMap GIS software. Field data were collected between 18 June 2007 and 16 July 2007 and due to technical difficulties, three sample points were not collected, leaving 147 for subsequent analysis (Figure 3). Sample points were navigated to using a Trimble GeoXH GPS receiver (+/- 0.30 m @ 95% CI after post-processing using Trimble H-star technology). Once at the pre-designated sample point, a 10 m x 10 m plot was centered over each point with the edges of the plot aligned in the cardinal directions. Percent cover estimates were made for each 100 m^2 plot using the point-intercept method (Herrick, et al 2005). Two 10 m line transects were positioned perpendicular to each other and crossing at plot center (i.e., the 5.0m mark of each line transect). Observations of cover type were made every 0.20 m along each 10 m transect, beginning at 0.10 m and ending at 9.90 m (n = 50 points for each line and n = 100 points for each plot). The first layer of canopy observed from nadir at each observation point was recorded as either: bare ground, rock ($\geq$75 mm), litter, dead herbaceous material, standing dead woody material, live herbaceous species, or live shrub. Rock that was < 75 mm was recorded as bare ground. While the focus of this study was the detection of bare ground, ground-cover types other than bare ground were recorded to better understand the spectral dynamics within each pixel.

Image Acquisition and Pre-processing

Multispectral satellite imagery was collected over the study area on June 17th and June 29th, 2007. This range of dates temporally coincided with ground sampling efforts during that year. SPOT 5 was acquired on June 29th which collects data in four spectral bands from the visible (545nm band center) through the near-infrared (NIR, 840nm band center) and short-wave infrared (SWIR, 1665nm band center) regions of the electromagnetic spectrum. The green, red, and NIR bands have a spatial resolution of 10 m while the SWIR band has a spatial resolution of 20 m (note: the SWIR band was resampled by SPOT image corporation to 10 m prior to delivery). ASTER imagery was acquired on June 17th which collects data in 14 spectral bands from the visible (560nm band center) to the thermal infrared (TIR, 11300nm band center for band 14). The spatial resolution of ASTER images vary by band: 15 m for all (3) visible and NIR bands, 30 m for all (6) SWIR bands, and 90 m for all (5) TIR bands. The SWIR bands were resampled to 15 m to match the resolution of the VNIR bands using ESRI's ArcGIS software and nearest neighbor resampling algorithm. The TIR bands were not used in this study.

SPOT 5 and ASTER data were delivered as level 1A and 1B (radiometrically corrected), respectively. SPOT 5 data were processed to reflectance by performing an atmospheric correction using the Cos(t) image-based absolute correction method (Chavez 1988) in Idrisi Andes software (Clark Labs, Worcester, MA). ASTER data were converted to radiance at the sensor using published conversion coefficients (Abrams et al. 1999). The radiance data was then converted to top of atmosphere (TOA) reflectance (using mean solar exoatmospheric irradiance (ESUN) for each band as reported by Thome et al. (2001) and the standard Landsat TOA equation from the Landsat 7 Science Data Users Handbook (Williams 1998). All imagery was geo-rectified to the study area and co-registered using ESRI's ArcMap and national agricultural imagery program aerial photography (2004) with 1 mpp resolution as well as high resolution aerial imagery (2005) with 0.05 mpp resolution with an absolute accuracy of +/- 0.015m based upon surveyed ground control points. Nearest neighbor resampling was used in all cases and the RMSE was 3.15 and 4.44 for the SPOT and ASTER imagery, respectively.

Image Processing

<u>Normalized Difference Vegetation Index</u>

The Normalized Difference Vegetation Index (NDVI) was calculated using both SPOT and ASTER datasets and the respective NDVI results were regressed against *in situ* bare ground measurements to determine the level of agreement between known bare ground exposure and vegetation index values. Vegetation indices have been previously correlated to bare ground exposure in semi-arid environments (McMurtrey et al. 1993) suggesting this simple technique has merit and for this reason was included in this study.

<u>Angle Index</u>

Roberts et al. (1993) noted that non-photosynthetic vegetation (NPV; i.e., litter) and bare ground may not be separable using multispectral sensors because of cellulose absorption within the bandwidths employed by multispectral sensors (van Leeuwen and Huete 1996). However, recent developments of two angle indices, the Angle at Near-Infrared (ANIR) and the Shortwave Angle Slope Index (SASI) offer some promise for discriminating NPV from soil by exploiting the information contained within multispectral imagery and uncovering band relationships between bands instead of relying solely upon reflectance data (Khanna et al. 2007). The ANIR index was calculated using SPOT 5 data following methods described in

Khanna et al. (2007). SASI could not be calculated with SPOT 5 data as its SWIR band does not extend out to 2200nm as required for this index. However, the SASI was determined using ASTER imagery. Calculation of these indices was performed using ESRI's ArcMap and resulting values at each field sample location were extracted to a database table for statistical analysis and comparison with ground truth values.

<u>Spectral Mixture Analysis</u>
Using RSI's ENVI, the Minimum Noise Fraction (MNF) transformation was performed using SPOT 5 imagery as a data reduction technique to uncover data dimensionality and segregate noise in the data (Boardman and Kruse 1994). Since MNF bands were required for further image analysis using spectral mixture analysis, this step was used to determine if all MNF bands (based upon dimensionality) were required for future processing and analysis.

In order to preserve full data dimensionality, four output MNF layers were used to match the number of bands in the SPOT 5 imagery. The MNF transformation used the shift difference method (Ifarraguerri and Chang 2000) for calculation of noise statistics. This method uses local pixel variance to estimate noise. The results of the MNF transformation were then used for additional spectral mixture analysis (SMA) processing with the next step being an investigation of pixel purity.

By randomly and repeatedly projecting scatter plots of the four MNF bands in n-Dimensions (in this case 4-dimensions), the pixel purity index (PPI) counts the number of times that each pixel is marked as a possible pure end-member at the extreme end of each projected vector. A threshold value of 3.0 was chosen to specify the minimum number of pixels that were marked at the ends of each projected vector. The number of iterations performed was 25,000 and a PPI image was created from this process in which an individual pixel's value represented the number of times that pixel was chosen as a possible pure end-member pixel. The maximum number of pixels used by the n-Dimensional Visualizer (n-DV) was set at 10,000. This allowed for visualization of the best PPI pixels but did not encumber the visualization process with too many pixels.

SMA or Linear Spectral Un-mixing assumes a mixed pixel can be modeled as a linear combination of spectrally pure end-members. To determine the composition of a mixed pixel requires the pixel to be broken down into its fractional proportion relative to each target end-member (Roberts et al. 1993, Settle and Drake 1993, Adams et al. 1995). Based upon these assumptions, the bare ground end-members derived from the PPI and n-DV were used to partially un-mix the SPOT 5 imagery into a fractional bare ground exposure layer. The SMA results were then regressed against ground truth data for evaluation.

Spectral Angle Mapper (SAM) classifies imagery by calculating the angle between each pixel to the end-member spectral vectors in n-dimensional space (where n = number of bands). Smaller angles represent better matches with the target end-member spectra (Kruse et al. 1993) and the best match is considered the most probable identification of that pixel. The bare ground end-members derived from PPI and n-DV were used for SAM classification. The results of this classification were regressed against ground truth data for evaluation.

Error Assessment

Since no classification was performed using NDVI, the accuracy of this approach was estimated using linear regression analysis to calculate correlation between NDVI values and known bare ground exposure.

The bare ground models derived from angle indices produced a classified layer of bare ground/non-bare ground by applying the threshold values described by Khanna et al. 2007. Producer accuracy was then calculated from the classified model.

To determine the ability of both SMA and SAM classifiers to accurately detect bare ground exposure in semi-arid rangelands using multispectral imagery, linear regression analyses were evaluated with particular attention given to the resulting coefficient of determination (R^2).

RESULTS AND DISCUSSION

Field data collection

Only ten percent of all 2007 field samples (n = 14) had >50 % exposed bare ground while 77% of these samples (n = 113) had bare ground exposure <=35 %. Based upon the research presented by others (Booth and Tueller 2003, Palmer and Fortescue 2003, Washington-Allen et al. 2006, Gokhale and Weber 2006) the majority of field training sites collected for this study had target levels below the suggested minimum threshold for reliable detection. However, the previous studies did not apply spectral un-mixing techniques (e.g., Gokhale and Weber [2006] used the maximum-likelihood classifier) which may be capable of improving target detection threshold levels.

NDVI

NDVI has poor correlation with bare ground exposure as the coefficient of determination (R^2) was only 0.187. The use of NDVI to classify bare ground was not explored further.

Angle Indices

As the amount of bare ground exposure increases, both ANIR and SASI indices were expected to increase (Khanna et al 2007). In this study, the ANIR values derived from SPOT5 imagery (2.91 to 3.13) follow this trend as do the ANIR (2.03-2.57) and SASI (-0.085 to 0.017) values derived from ASTER imagery, although only marginally in all cases. Khanna et al (2007) classified every pixel with an ANIR value of 2.4 or higher and a SASI value of -0.01 and higher as “soil, residue and low-leaf area index vegetation.” Using SPOT5 ANIR values classified all ground truth sites (n=147) as bare ground sites including those where no bare ground was found in the field (n=15, or approximately 10% of all sample sites). Using ASTER ANIR values resulted in seven sites known to have no bare ground exposure classified as a bare ground site, while the majority of known non-bare ground sites were correctly classified (53%; Table 1). It is interesting that when bare ground exposure exceeds 10%, the ASTER ANIR classification improved steadily.

Table 1. Distribution of classified pixels in the bare ground model produced using the ANIR index (ASTER imagery) and threshold values suggested by Khanna et al (2007)

	Known bare ground exposure				
	0	**10**	**20**	**30**	**40**
Bare ground class	0.47	0.76	0.80	0.50 a	0.50 a
Non-bare ground class	0.53	0.24	0.20	0.50 a	0.50 a

a. These results based upon sample size of one.

Similar to the SPOT5 ANIR classification, the classification using ASTER SASI values classified all (n=147) ground truth sites as a bare ground area. As a result, both SPOT5 ANIR and ASTER SASI classifications were considered unreliable as they grossly overestimated bare ground exposure at the O'Neal study area.

Spectral Mixture Analysis

Visual examination of the four resulting MNF bands did not demonstrate noticeable degradation of image quality for any of the MNF bands suggesting that a spatial coherence threshold was not reached (Figure 2) with either the multispectral SPOT 5 or ASTER imagery and these data could not be further reduced. Therefore, all four MNF bands were selected as input bands for further image processing.

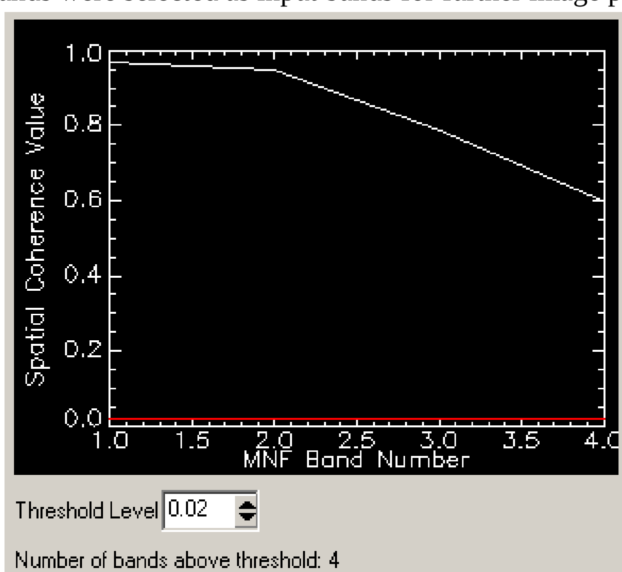

Figure 2. Example of spatial coherence threshold testing with ENVI software (SPOT 5 data is shown in this illustration).

End-member Selection

The results from pixel purity index (PPI) analysis were used in the n-Dimensional Visualizer (n-DV) to retrieve end-members. The n-DV plots the pixels as a scatter plot (pixel cloud) that can be viewed and rotated in minimum noise fraction (MNF) space with the number of dimensions being equal to the number of MNF bands used (e.g., four in the case of SPOT imagery). The purest pixels plot at the corners of the scatter plot and form candidate end-members. However, none of the candidate end-member pixels coincided with areas where field data was available and as a result, these candidate end-members could not be validated directly. To validate these pixels as bare ground end-members, the spectral signatures of the candidate end-members were extracted and compared to reflectance signatures of known bare ground pixels within the study area. As a result, the spectral signatures for the candidate end-members were accepted and a spectral mixture analysis classification completed.

Regressions between spectral mixture analysis models of bare ground exposure and known percent bare ground revealed weak coefficients of determination when using either SPOT (R^2 = 0.243) or ASTER imagery (R^2 = 0.179) (Figures 3 and 4)

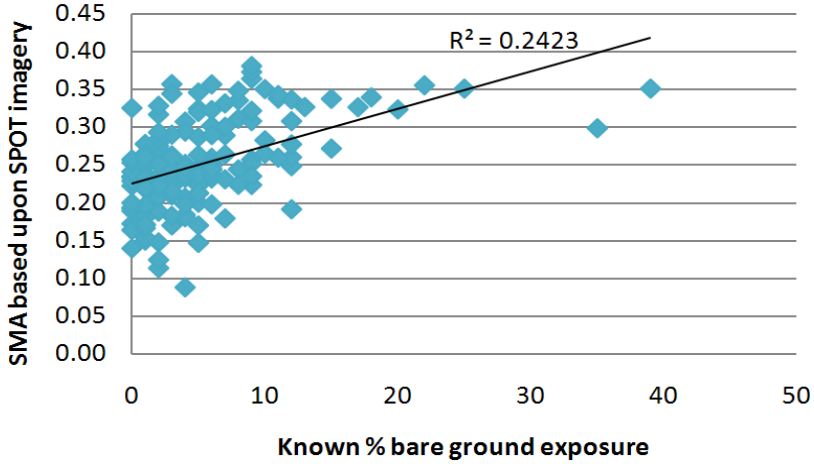

Figure 3. Regression between SMA scores for bare ground training sites and known bare ground exposure using SPOT satellite imagery.

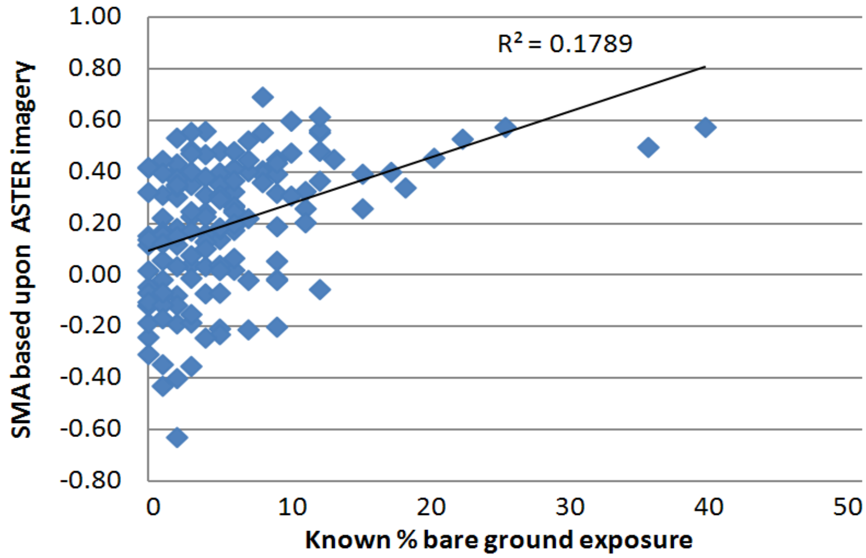

Figure 4. Regression between SMA scores for bare ground training sites and known bare ground exposure using ASTER satellite imagery.

Spectral Angle Mapper

The resulting relationship between SAM scores of bare ground and known bare ground exposure were very low (R^2 = 0.133). No further exploration into the use of SAM was conducted (figure 5).

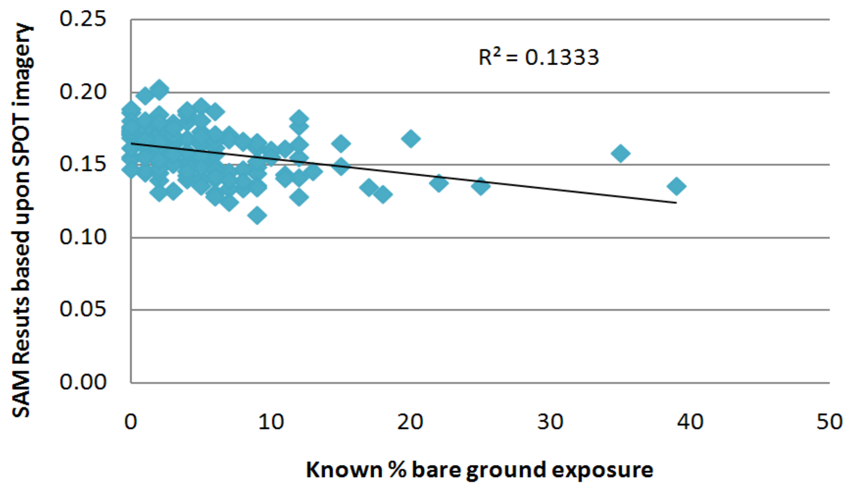

Figure 5. Regression between SAM scores for bare ground training sites and known bare ground exposure using SPOT satellite imagery.

CONCLUSIONS

This study provides an exploration into the potential of various indices and sub-pixel analyses to detect and reliably classify bare ground exposure in semi-arid rangelands using two common multispectral platforms (SPOT 5 and ASTER), where bare ground is relatively rare (<35%). The results of these explorations suggest that none of the techniques tested (NDVI, SASI, SMA, and SAM) have the potential to provide an accurate model of bare ground save for the ANIR index.

The ANIR index was calculated using ASTER imagery (SPOT 5 imagery cannot support this index) and results suggest that bare ground may be detectable at levels as low as 10% exposure. Further research is required to verify this possibility.

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Effect of Coregistration Error on Patchy Target Detection using High-Resolution Imagery

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ABSTRACT

Many factors influence classification accuracy and a typical error budget includes uncertainty arising from the 1) selection of processing algorithms, 2) selection of training sites, 3) quality of orthorectification, and 4) atmospheric effects. With the development of high spatial resolution imagery, the impact of errors in geographic coregistration between imagery and field sites has become apparent -- and potentially limiting-- for classification applications, especially those involving patchy target detection. The goal of this study was to document and quantify the effect of coregistration error between imagery and field sites on classification accuracy. Artificial patchy targets were randomly placed over a study area covered by a QuickBird image. Classification accuracy of these targets was assessed at two levels of coregistration. Results showed that producer's accuracy of target classification increased from 37.5% to 100% between low and high levels of coregistration respectively. In addition, "Error due to Location", a measure of how well pixels were located within respective classes, decreased to zero at high coregistration levels. This study highlights the importance of considering coregistration between imagery and field sites in the error budget, especially with studies involving high spatial resolution imagery and patchy target detection.

KEYWORDS: Quickbird, coregistration, field sites, positional accuracy, classification accuracy, patchy targets

INTRODUCTION

Much has been written about the effect of various input parameters and processing decisions on resulting image classification accuracy. Toward that end, researchers have investigated and published details describing the 1) selection of appropriate classification algorithms (Foody & Arora, 1997), 2) effect of the purity of training sites relative to a minimum ground cover threshold (Mundt et al., 2006), 3) influence of the orthorectification process (Cheng et al., 2003; Robertson, 2003; Toutin & Chenier, 2004; Wijnant & Steenberghen, 2004; Parcharidis et al., 2005), 4) impact of misregistration between image layers (Townshend et al., 1992; Dai & Khorram, 1998; Stow, 1999; Roy, 2000; Verbyla & Boles, 2000; Wang & Ellis, 2005), 5) influence of spectral resolution (Mehner et al., 2004), as well as the 6) influence of atmospheric anomalies and correction processes (Lillesand & Kiefer, 2000). The result of these and other efforts has allowed geospatial scientists to construct a fairly complete error budget and, thereby, better understand and interpret image classification results.

With the development and proliferation of high spatial resolution imagery (i.e., QuickBird and IKONOS) and positioning technologies that readily enable highly accurate training site location (i.e., sub-meter resource-grade GPS), another segment of the error budget has become apparent; geographic coregistration between imagery and field sites (i.e., training and validation samples). Prior to the development of high spatial resolution technologies, it was fairly easy to correctly locate a field site within the correct pixel of existing imagery (such as Landsat with 28.5 m x 28.5 m pixels) using even uncorrected GPS locations. Today, however, it has become a challenge to reliably locate training sites within the correct and representative pixel (Weber, 2006). Further, as we explore the ability of remote sensing technologies to detect patchy and rare land features (e.g., those that may occupy only one QuickBird or IKONOS pixel), it is not only important but critical that field sites be placed within the correct pixel if one expects results with reliable accuracy ($\geq$ 75% overall accuracy; Goodchild et al., 1994). However, accurate field site positioning may become less critical when target features grow larger and occupy numerous, contiguous pixels. The purpose of our research was to explore the effect of geographic coregistration between imagery and field sites (henceforth referred to as coregistration) as it relates to the detection and accurate classification of patchy and rare land features.

To our knowledge, no study has been performed to quantify the effect of this type of coregistration error on classification accuracy. However, Sanchez & Kooyman (2004) described limitations for classification of penguin habitat in Antarctica due to the positional accuracy of QuickBird imagery. This was not quantified, and the error examined was not coregistration between imagery and field sites, but rather the effect of image coregistration alone.

The potential significance of a coregistration effect was first noticed in the authors' work while using QuickBird and SPOT 5 multi-spectral imagery to produce predictive presence and distribution models of a patchy invasive weed, leafy spurge (*Euphorbia esula*), at study sites in southeastern Idaho (Weber et al., 2006). The authors acquired QuickBird and SPOT 5 imagery during a time period when leafy spurge was believed to be most spectrally distinct from the matrix of other species and cover types (i.e., the pre-flowering and flowering stage). Using the location of known leafy spurge infestations (+/- 0.9m @ 95% CI), the authors applied a maximum-likelihood classifier to produce predictive presence/absence models of leafy spurge. The results indicated that QuickBird multispectral imagery could not produce reliable models ($\geq$ 75% overall accuracy; Goodchild et al., 1994) in contrast with the models derived from SPOT

5 imagery which did produce reliable results (76%). The authors sought answers to explain why QuickBird imagery did not perform as well as SPOT 5 imagery under those conditions. What was most puzzling was the fact that the QuickBird sensor appeared to be far more technologically advanced compared to all other multispectral sensors available at that time (2003). The QuickBird sensor had far better 1) radiometric resolution (11-bit compared to 8-bit), 2) spatial resolution (2.4 m compared to 10 m), 3) comparable spectral resolution (blue, green, red, and near-infrared compared to SPOT's green, red, near-infrared, short-wave infrared), and 4) very good signal-to-noise ratios. Yet, the models derived from the QuickBird imagery failed to achieve the same level of accuracy as those derived from the "simpler" SPOT 5 imagery.

The differences between the platforms were categorically addressed and new predictive models created for comparison: 1) imagery was converted from 11-bit to 8-bit by performing a linear histogram stretch, 2) imagery was resampled to produce a QuickBird product with 10m spatial resolution (using cubic convolution resampling) and thereby absorb georegistration errors, and 3) classifications were performed using only those bands in common between QuickBird and SPOT 5 platforms (green [560 nm versus 545 nm band centers, respectively], red [660 nm versus 645 nm band centers, respectively], and near-infrared [830 nm versus 840 nm band centers, respectively])(note: these "common bands" allowed the authors to produce and use vegetation indices such as NDVI). After each adjustment was made, another classification was performed, producing a new presence/absence model for leafy spurge. In each case, the SPOT 5 imagery out-performed the QuickBird imagery. The only discrepancy that helped explain the performance difference was the fact that SPOT 5 imagery appeared to be better georeferenced (however, this was not quantifiable due to the remote nature of the study area and lack of ground control features). It was at this point that the authors designed an experiment to test and quantify the effect of coregistration error between imagery and field sites on classification accuracy. The paper focuses on a description of the experiment and its results.

METHODS

Study Area

The experiment was performed in sagebrush-steppe rangelands of southeastern Idaho approximately 30 km south of Pocatello, Idaho, at the O'Neal Ecological Reserve. The O'Neal Ecological Reserve (http://www.isu.edu/departments/CERE/o'neil.htm) was donated to the Department of Biological Sciences by Robin O'Neal. This 50 ha site, located along the Portneuf River, contains riparian areas along the river and typical sagebrush steppe upland areas located on lava benches. The O'Neal Ecological Reserve receives <0.38 m of precipitation (primarily in the winter) annually and is relatively flat with an elevation of approximately 1400 m (1401-1430 m). The dominant plant species is big sagebrush (*Artemisia tridentata*) with various native and non-native grasses, including indian rice grass (*Oryzopsis hymenoides*) and needle-and-thread (*Stipa comata*).

Field Data

Throughout the study area we placed 22 bright blue tarps (2.4m x 3.0 m) approximately equal in size to a single QuickBird pixel (2.4 x 2.4 m) (Fig. 1). The positioning of the tarps was random but with the following set of criteria established for final placement in the field 1) no part of the tarp was placed beneath vegetation, 2) tall vegetation (>1m) was not located near the tarps (+/-2m) that could cast a shadow on a portion of the tarp during image acquisition, and 3) tarps were installed flat and horizontal to avoid deformation and changes in their apparent size within the imagery. The location of the tarps was taken using a Trimble ProXR GPS receiver and post-processed using base station files from Pocatello, Idaho (+/- 0.9m @ 95% CI) (Serr et al. 2006). QuickBird imagery was ordered and acquired while the tarps were in the field. When the imagery was delivered, the tarps were removed from the field.

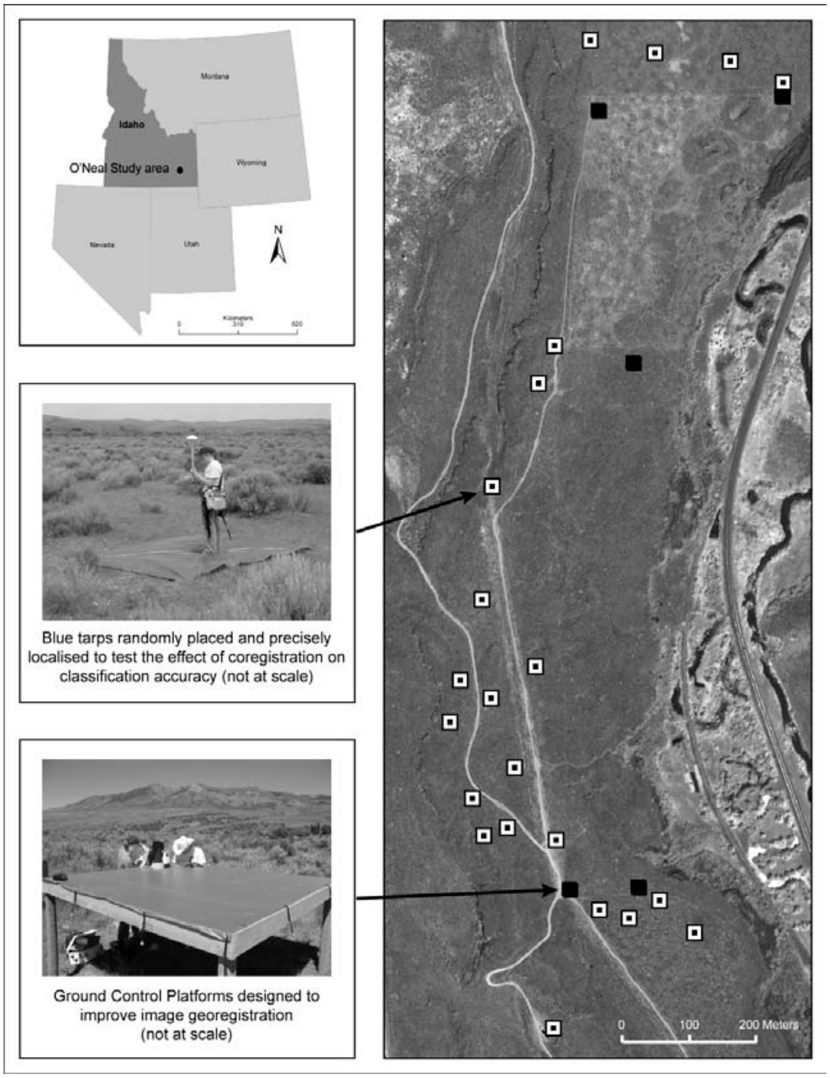

Figure 1. The study site, location of blue tarps used for classification, and ground control platforms (with silver tarps) used for georectification.

In order to compare spectral properties of blue tarps with common rangeland elements, spectral signatures of various targets were acquired using an Analytical Spectral Device (ASD) hand-held FieldSpecPro field spectroradiometer. Measurements were made during a sunny day (without clouds) at +/- 1 hour of solar noon. For each target, between 15 and 25 spectral recordings were taken. Spectral comparison included blue tarps, bare ground, basalt, low sagebrush (*Artemisia arbuscula*), and big sagebrush (*Artemisia tridentata*).

To improve georegistration of the imagery within the relatively flat study area we constructed five permanent ground control platforms (Fig. 1). Each platform was 2.4 m x 2.4 m in size and stood 1.2 m above the ground. During satellite image acquisition periods, highly reflective silver tarps were tightly secured to the platforms. The location of the platform's corners were acquired and processed with Trimble ProXR receivers in the same fashion as noted above (+/- 0.9m @ 95% CI). All five ground control platforms were used to georectify the Quickbird imagery used in this study.

Imagery

Standard QuickBird imagery (28-June-2006) was delivered by DigitalGlobe Corporation projected into Idaho Transverse Mercator. The authors georectified the imagery using the ArcGIS 9.1 georectify tool. All five ground control platforms were clearly visible within the imagery making the positioning of control points quite easy. In this case, the "from" location was on-screen digitized and the "to" location was entered from the keyboard using the known GPS-based locations. Georectification was performed using a first order affine transformation with cubic convolution resampling.

Frequently, imagery is atmospherically corrected before georectification is performed to best preserve the original radiometric data. However, since the imagery was already projected upon delivery, the authors chose to perform atmospheric correction twice, once using the standard imagery as delivered and again using the georectified imagery. Atmospheric correction was performed with Idrisi Kilimanjaro (v14) using the ATMOSC module. All imagery was corrected using the Cos(t) model (Chavez, 1996) with input parameters reported in the metadata supplied by DigitalGlobe Corporation. Both the georectified and standard images (bands 1-4) were atmospherically corrected yielding four distinct datasets for use in this experiment: 1) standard imagery as delivered (standard), 2) standard imagery that was atmospherically corrected (atmos), 3) georectified imagery (geo), and 4) georectified imagery that was atmospherically corrected (geo-atmos).

A geodatabase feature class containing 50 points representing the location of the "target" blue tarps (n=22) and non-target points (n=28) was randomly resampled without replacement using Hawth's tool in ArcGIS 9.1. This produced two datasets for use in the classification process. The first (n=28) was used as training sites (14 blue tarp and 14 non-target points) and the second (n=22) was used as validation sites (8 blue tarp and 14 non-target points)(note: ideally 14 blue tarps would have been available for validation, however based upon the author's tarp positioning criteria, a total of only 22 tarps could be positioned in the field and remain in place throughout the satellite acquisition time window of approximately one month). Spectral signatures were extracted from each of the four imagery datasets (standard, atmos, geo, and geo-atmos) using the training site points within the MAKESIG module in Idrisi Kilimanjaro.

A series of maximum-likelihood classifications (Richards 1986) were performed using Idrisi Kilimanjaro (MAXLIKE) and validated using the ERRMAT module, which calculates both a standard contingency table (Congalton & Green, 1999) and Kappa statistic (Kappa Index of Agreement [KIA]) (Cohen, 1960; Titus et al., 1984; Foody, 1992; Monserud & Leemans, 1992). To better identify the source of classification error, the VALIDATE module of Idrisi was also used, which calculates a variety of statistics quantifying agreement between a classified image and reference image relative to the 1) quantity of cells in each class and 2) location of cells in each class (Pontius, 2000). The reference image was a raster layer of the validation sites. The "Error due to Location" statistic is reported here as it indicates how well pixels are located within each class, and hence, best communicates the results of this study.

RESULTS AND DISCUSSION

The root mean square error (RMSE) reported during the georectification process of the QuickBird imagery was 0.20 m. True horizontal positional error was determined by measuring the distance from the known location (determined using GPS) to the center of each blue tarp's location within the imagery. This calculation was performed twice, once using the standard imagery and again using the georectified imagery. The mean distance between the known blue tarp locations and 1) its location within the standard imagery was 1.55 m (median = 1.61 m) and 2) its location within the georectified imagery was 0.80 m (median = 0.55 m) (Fig. 2). The latter error was <50 % of the size of each QuickBird pixel while the former was >50 % of the size of each pixel. The measured difference in positional accuracy was tested using a paired t-test and Wilcoxon Signed Ranks and the improvement was found to be significantly different ($P < 0.0001$). Further, this difference is notable as other authors have hypothesized that field site locational error must be <50 % of the pixel size to yield reliable classification results (Peleg & Anderson, 2002; Weber, 2006), particularly in the case of patchy target detection. For instance, if a patch of leafy spurge covers only the area of a single QuickBird pixel, then a shift in the correct location of the field site –relative to the satellite imagery— of as little as half a pixel can not only lower classification accuracy but introduce a misclassification error into the spectral signatures that will propagate throughout the classification process when field sites are positioned over an entirely different class.

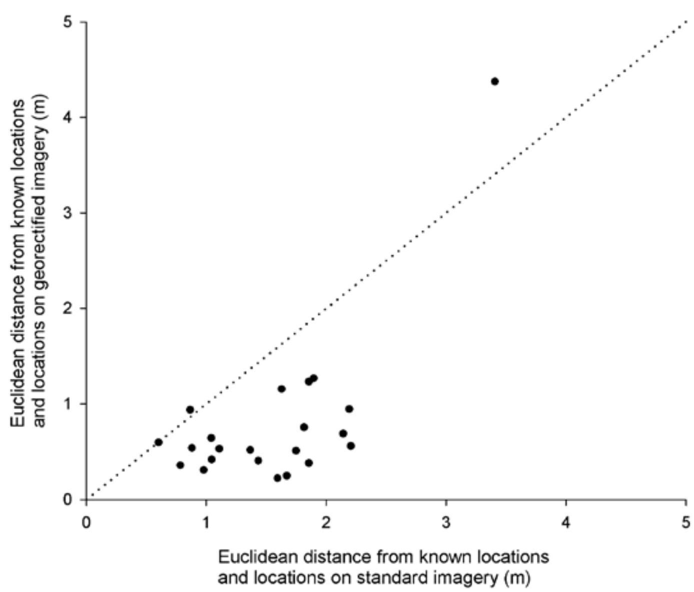

Figure 2. Euclidean distance from known locations and the location of points (n=22) determined from georectified (mean and median = 0.80 and 0.55 m respectively) and standard QuickBird imagery (mean and median = 1.55 and 1.61 m respectively). The dotted diagonal line represents a hypothetical 1:1 relationship where no difference between standard and georectified locations would be measurable.

The result of the maximum-likelihood classifications are given in Table 1(a-d). The classification results presented under sections a and c reveal a precision effect; that is the effect of coregistering imagery relative to the location of "known" field site locations used in the classification-validation process. By reducing the horizontal positional error between the target's true location relative to its location within the imagery, we were able to improve producer's accuracy from an unacceptable 37.5 % to a very reliable 100 %. User accuracy was reduced during the georectification process (100 % to 89%). However, upon closer inspection one can see that when using standard imagery (Table 1a), only 3 of the 8 blue tarp locations were detected, albeit each was correctly detected. A user would be able to find the three targets but would be blind to over 50 % of the target population. Using the georectified imagery (Table 1c), users would find 100 % of the target population and only one false-positive site. The latter is actually a much better scenario of operation for weed managers or other users of predictive maps.

Table 1. Error matrix describing maximum-likelihood classification results for detection of randomly placed blue tarps (a rare, patchy target) using QuickBird multispectral imagery.

	Known ground truth			
	Blue tarp target	Non-target	Total	Commission Error
a) Standard imagery				
Blue tarp target	3	0	3	0.000
Non-target	5	14	19	0.263
Total	8	14	22	
Omission Error	0.625	0.000		Overall error 0.227
KIA = 0.43; Error due to Location = 0.00*				
b) Atmospherically corrected standard imagery				
Blue tarp target	0	4	4	1.000
Non-target	8	10	18	0.444
Total	8	14	22	
Omission Error	1.000	0.286		Overall error 0.546
KIA = -0.32; Error due to Location = 0.36				
c) Georectified imagery				
Blue tarp target	8	1	9	0.111
Non-target	0	13	13	0.000
Total	8	14	22	
Omission Error	0.000	0.071		Overall error 0.046
KIA = 0.90; Error due to Location = 0.00*				
d) Atmospherically corrected georectified imagery				
Blue tarp target	8	1	9	0.111
Non-target	0	13	13	0.000
Total	8	14	22	
Omission Error	0.000	0.071		Overall error 0.046
KIA = 0.90; Error due to Location = 0.00*				

Where KIA is the Kappa Index of Agreement

** indicates the spatial allocation of the pixels is as accurate as possible relative to the validation sites (Pontius, 2000).*

The "Error due to Location" statistic further corroborated the inferred results. Where georectification was < 50 % the size of a pixel, "Error due to Location" was zero, indicating that none of the disagreement between the predictive model and the reference image was due to locational error. In comparison, "Error due to Location" was as high as 36% in the case of the atmos imagery dataset (Table 1b) (Pontius, 2000).

No additional improvement in overall classification accuracy was seen using the atmospherically corrected data. This is principally because there was little potential for improvement as only one of the 22 target sites was incorrectly classified. These results should not be interpreted to indicate that atmospheric correction is unimportant, but rather that the effect of coregistration plays a significant role in a classification's error budget.

Results from this study underline the impact of coregistration error. In this study, blue tarps were used to simulate homogeneous patchy targets, and while these targets were artificial, we investigated the spectra of these targets relative to adjacent, natural targets to better understand the classification results. Fig. 3 shows the spectra of the blue tarps has some similarities with adjacent, natural targets like sagebrush and bare ground, especially in the red and near-infrared regions. As a result, reducing coregistration error should benefit classification results of other natural patchy targets. However, the authors acknowledge another important factor influencing patchy target detection, target cover thresholds (Mundt et al., 2006). In this study, the targets (blue tarps) had 100% ground cover whereas many natural, patchy targets will exhibit a much lower ground cover making accurate classification more challenging. Other studies have developed methods to reduce the impact of positional error using spatial aggregation (Carmel et al., 2006) and epsilon band in a change detection context (Mas, 2006). However, these techniques may be of limited application in the context of patchy target detection (i.e. where target size is approximately the same as pixel size) due to the critical loss spatial resolution during aggregation and the subsequent loss of information.

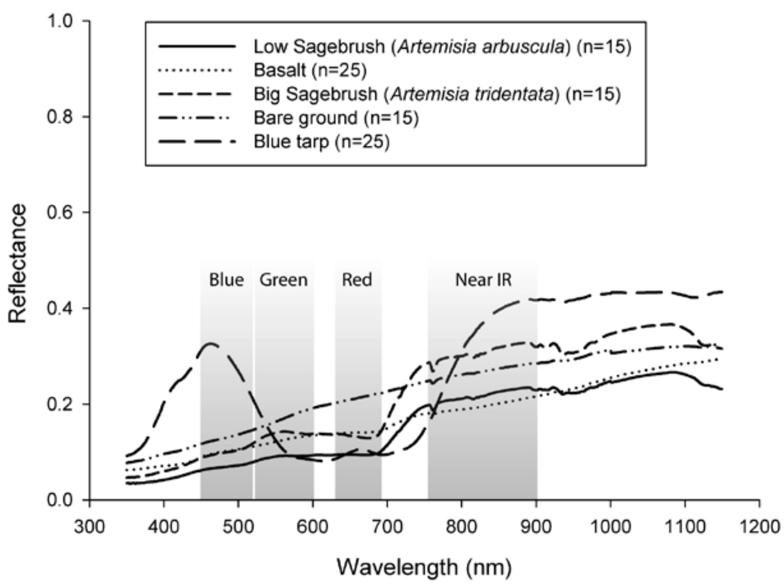

Figure 3. A comparison of spectral signatures from common rangeland targets and the artificial blue tarps used in this study. Signatures were acquired with a spectroradiometer and the mean signature of n (15-25) spectra are shown. QuickBird image bands are shown in grey for reference.

This study was performed at the QuickBird spatial resolution as this sensor highlighted the challenge to accurately locate field sites within the correct and representative pixel. In semi-arid environments, this accuracy is critical because landscape features such as sagebrush, shrubs, patches of invasive weeds, and patches of bare ground are frequently found at the same spatial order (i.e., 1-4m). The authors hypothesize that the coregistration effect described in this paper will diminish as the size of the pixel increases and the likelihood of field sites "automatically" being incorporated into the correct/representative pixel increases. As a result, coregistration error will be nil where field site positional error is small in proportion to a pixel's size.

CONCLUSIONS

Coregistration error between imagery and field sites is an important consideration when evaluating classification results. With the development and proliferation of high spatial resolution imagery, a need arises to use high accuracy positioning technologies to ensure that field sites are correctly located within the representative pixel(s). Without appropriate allowances, classification accuracy may be seriously hindered especially when attempting to detect patchy and rare targets on the landscape.

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Local-scale Validation of the Surface Observation Gridding System with *In Situ* Weather Observations in a Semiarid Environment

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ABSTRACT

While the Surface Observation Gridding System (SOGS) provides spatially continuous models of meteorological conditions, little work has been done to independently validate SOGS data for site-specific research and as a result, a single nearby weather station is commonly selected instead. This study sought to determine 1) local-scale accuracy of SOGS data through correlation with independent, *in situ* weather station measurements, and 2) local-scale accuracy of SOGS data relative to a nearby weather station. Correlations between SOGS data and *in situ* weather observations and between *in situ* weather observations and a nearby weather station were examined in a semi-arid environment of southeastern Idaho over the 2006 growing season. Results indicate both SOGS and nearby weather station data were significantly correlated with *in situ* weather station measurements. While temperature correlations between *in situ* and the nearby weather station were slightly greater compared to SOGS, SOGS data appeared to be a better predictor of precipitation. This suggests the use of a nearby weather station is appropriate for local temperature parameters, but precipitation parameters are better estimated using SOGS data. Overall, the validation of the SOGS weather models closely agreed with independent, *in situ* weather measurements and as a result, greater confidence can be placed in the accuracy of the productivity, biomass, and global climate change models derived from these data.

KEYWORDS: raster, climate, SOGS, global climate change

INTRODUCTION

Models of climate and meteorological conditions are important to our understanding of various ecosystem processes and driver variables like primary productivity. However, accurate spatially-continuous climate models with high-temporal resolution (e.g. daily) are rare (Running *et al.* 1987, Thornton *et al.* 2000) leaving research scientists no alternative but to use 'locally' available weather station data. These data are assumed to accurately characterize 'nearby' study sites, but this assumption may go untested. In some cases, the assumption is valid especially where the study site is reasonably close to the weather station and in areas of minimal topographic relief. In other cases, this assumption is questionable when study sites are more distant from weather stations and in mountainous areas of high topographic relief. In such areas, temperature, humidity, and precipitation are all influenced by differences in elevation resulting in weather events that are sometimes vastly different than those found at 'nearby' weather station.

The most recent development of spatially-continuous, global primary productivity models are those derived from the Moderate-resolution Imaging Spectroradiometer (MODIS). MODIS is a high-temporal resolution sensor aboard the National Aeronautics and Space Administration (NASA) Earth Observing System Terra and Aqua satellites which were launched into space in 1999 and 2002, respectively. The MODIS sensor captures data in 36 spectral bands (0.4 µm to 14.4 µm) and at various spatial resolutions ranging from 250 m to 1000 m. MODIS images the entire Earth every 1 to 2 days and was designed to provide broad-scale measurements of global dynamics (NASA 2007a). As a result of these advances, the reliable production of repeatable and consistent measures of the global terrestrial ecosystem began (Running *et al.* 2004).

With the availability of satellite measurements of global vegetation, weekly global gross primary productivity (GPP) models became possible (Running *et al.* 2004). Subsequently, weekly GPP could then be used to calculate global annual net primary productivity (NPP) (Running *et al.* 2004). These products are relevant to global climate change as more than one climate study has suggested that temperature increases due to the radiative forcing caused by increased atmospheric carbon may lead to changes in ecosystem production (e.g., NPP) and plant species composition (Berry and Bjorkman 1980, Bounoua et al 1999). Such changes will necessarily alter primary productivity curves and may cascade other effects throughout the environment. For this reason, accurate climate and meteorological inputs are ever more important.

The NASA Data Assimilation Office (DAO) collects global surface weather data from all available weather sources and interpolates these point data to produce a raster dataset of the global climatic conditions at 1º by 1.25º resolution. This dataset is then used by MODIS algorithms to generate 1) daily 24-hour average temperature, 2) daily 24-hour minimum temperature, 3) actual vapor pressure, and 4) incident shortwave solar radiation (Running *et al.* 2004). These meteorological data are then used to generate daily GPP estimate at 1 km^2 resolution. The meteorological data, however, have not been well validated, especially at local scales, although other MODIS products have been validated including the MODIS-derived albedo values (Barnsley *et al.* 2000), MODIS bidirectional reflectance distribution function (BRDF), broadband albedos, nadir BRDF-adjusted reflectance (Liang *et al.* 2002), MODIS-based sea surface temperature (Minnett *et al.* 2002), MODIS Normalized Difference Vegetation Index, Leaf Area Index, fraction of absorbed photosynthetically active radiation (Huemmrich *et al.* 2005), and gross primary productivity (Heinsch *et al.* 2006).

Heinsch *et al.* (2006) demonstrated that the NASA DAOs GPP estimates had 28% error and noted that the DAOs global meteorological dataset plays an important role in the accuracy of the GPP algorithm (Heinsch *et al.* 2006). Moreover, another recent study indicated that the NASA DAOs GPP and NPP estimates were considerably different compared to other GPP and NPP estimates driven by meteorological data from European Centre for Medium-Range Weather Forecasts and National Centres for Environmental Prediction/National Centre for Atmospheric Centre (Zhao and Running 2006). This study also concluded that inaccurate meteorological data can introduce substantial error in the accuracy of the GPP and NPP estimates and emphasized the need to minimize these errors. Zhao *et al.* (2005) suggested that the difference in spatial resolution between the MODIS products and DAOs meteorological dataset had significant impacts on the GPP and NPP estimates and interpolated the DAOs meteorological data to the 1-km MODIS pixel level to improve the accuracy of the MODIS products.

Today, several important products derived from MODIS imagery (gross primary productivity [GPP] and net primary productivity [NPP]) use the Surface Observation Gridding System (SOGS) dataset (NTSG 2007). Jolly *et al.* (2005) first suggested the SOGS approach to improve the availability and accuracy of meteorological data. This approach uses a relational database to store point information and interpolates the meteorological conditions from point-source data to provide spatially-continuous meteorological raster layers (1000m x 1000m) such as daily minimum temperature, maximum temperature, precipitation, humidity, and solar input. The SOGS estimates are considered experimental (NASA 2007b) and thus far, SOGS as well as other meteorological inputs used to calculate MODIS products have only been evaluated and validated across the United States indirectly (i.e., using other derived models) and at coarse scales (Zhao *et al.* 2005, Jolly *et al.* 2005). While the reported accuracy of the validated meteorological inputs may be acceptable at regional or global scales, large inaccuracies might exist at a local scale, especially in terrain with large topographic variation or areas located along abrupt climatic gradient zones (Zhao *et al.* 2005). Consequently, site-specific, local-scale validation of the SOGS model is needed, especially in mountainous, semi-arid environments such as those found in southeastern Idaho.

Southeastern Idaho is a region where relatively flat high-desert plains exist (the Snake River Plain) alongside mountain ranges. The economy of this semi-arid region is varied, but geographically dominated by agriculture and ranching industries. For these reasons, southeastern Idaho is especially appealing for researchers concerned with the effects of drought, global climate change, and desertification on rangeland ecosystems. To fully understand these diverse rangelands and to enable accurate forecast of rangeland conditions, accurate weather models are imperative.

The objectives of this study were: 1) to determine the accuracy of SOGS meteorological data for site-specific, local-scale research projects in southeastern Idaho using independent, *in situ* weather station measurements, and 2) to determine if SOGS data are more accurate and, therefore, more appropriate to use, relative to meteorological data from a nearby weather station. The nearby weather station was also independent of the SOGS dataset and the data from this station was not used as part of the SOGS network. We present this paper as a case study that might be useful in further validating the recently-developed SOGS meteorological data at a local scale. This case study may also assist other local-scale studies choose the appropriate meteorological data as inputs for other models.

METHODS

Study Area

Data were collected at the O'Neal Ecological Reserve, an area of sagebrush-steppe rangelands in southeastern Idaho approximately 30 km southeast of Pocatello, Idaho (42° 42' 25"N 112° 13' 0" W), where many local-scale rangeland studies are being conducted (Figure 1). The O'Neal Ecological Reserve (http://www.isu.edu/departments/CERE/o'neil.htm) was donated to the Department of Biological Sciences, Idaho State University by Robin O'Neal. This 50 ha site, located along the Portneuf River, contains riparian areas in contrast with typical sagebrush steppe upland areas located on higher elevation lava benches. The O'Neal Ecological Reserve receives <0.38 m of precipitation annually (primarily in the winter) and is relatively flat with an elevation of approximately 1400 m. The dominant plant species include big sagebrush (*Artemisia tridentata*) with various native and non-native grasses and forbs, including indian rice grass (*Oryzopsis hymenoides*) and needle-and-thread (*Stipa comata*).

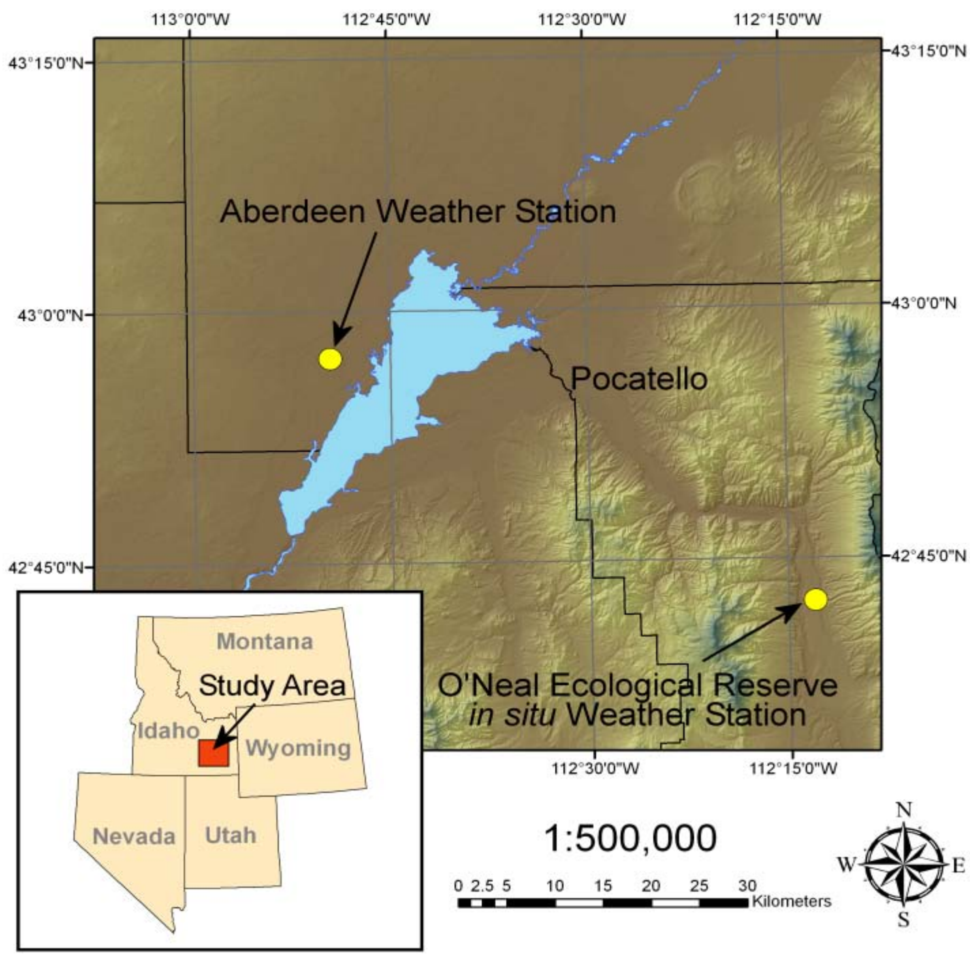

Figure 1. Location of the two independent weather stations used in this study.

In Situ Weather Station

Part of the instrumentation present at the O'Neal Ecological Reserve is a Davis Weather Station (http://www.davisnet.com). The Davis Vantage Pro2 sensor meets or exceeds the specifications set forth by the GLOBE program (http://www.globe.gov). GLOBE is an international science and education program that promotes the investigation of earth and environmental systems science by students, teachers, and scientists. To accomplish this vision, GLOBE has designed a number of data collection protocols, which include the collection of weather observations with Davis and other alternative equipment.

Since June-2006, the O'Neal weather station has measured and recorded observations every two hours describing temperature, humidity, barometric pressure, wind speed and direction, precipitation, solar radiation, solar energy, and soil moisture. In addition, the Vantage Pro2 weather sensor also calculates dew point, various heat indices, and evapotranspiration (ET_0). Evapotranspiration is calculated and recorded as hourly potential ET_0 (in mm) using measured and calculated variables (Jensen *et al.* 1990, Davis 2006). Specifications for all data measurement are given in Table 1. We used a 100-day sampling period beginning on 14-June-2006 and ending on 21-September-2006 for the comparison of SOGS weather data and the *in situ* weather data. This sampling period covered much of the growing season and captured peak biomass production.

Table 1. Specifications for the weather sensors used at the O'Neal Ecological Reserve (Davis Vantage Pro 2) and Aberdeen weather station, Idaho USA.

	O'Neal Ecological Reserve			Aberdeen Weather Station		
Measurement	**Setting**	**Resolution**	**Accuracy**	**Setting**	**Resolution**	**Accuracy**
Temperature	Celsius (˚C)	0.1 ˚C	+/-0.5˚C	Fahrenheit (˚F)	0.01 ˚F	+/-0.1 ˚F
Humidity	Percent (%)	1.0%	+/-5.0%	Percent (%)	0.01%	+/- 3.0%
Barometric pressure	Inches of mercury (Hg)	0.01" Hg	+/-0.03" Hg	---	---	---
Wind speed	Meters/second (m/s)	0.1 m/s	+/- 5.0%	Miles/ hour (mph)	0.01 mph	+/- 1.0%
Precipitation	Millimeters (mm)	0.2 mm	+/- 4.0%	Inches (In)	0.01"	+/- 0.5%
Solar radiation (global and diffuse)	Watt/square meter (W/m^2)	1 W/m^2	+/- 5.0%	Langleys (Ly)	0.01 Ly	+/- 5.0%
Solar energy	Langleys (Ly)	0.1 Ly	+/- 5.0 %	---	---	---

Aberdeen Weather Station

The Aberdeen weather station in southeastern Idaho was used as the independent, nearby weather station in this study. It is a part of Agrimet and the Pacific Northwest Cooperative Weather Network (http://www.usbr.gov/pn/agrimet/) and has been in operation since 20-March-1991. The station is located approximately 34 km northwest of Pocatello, Idaho (42° 57' 12"N 112° 49' 36" W, Elevation: 1341 m) and 57 km northwest of the O'Neal Ecological Reserve (Figure 1). The Aberdeen weather station is within an area of flat topography immediately adjacent to agricultural fields. The instrumentation present at the Aberdeen weather station measures temperature, relative humidity, wind speed and direction, precipitation, solar radiation, soil moisture, and soil temperature (http://www.usbr.gov/pn/agrimet/aginfo/station_params.html#abei). In addition, the Aberdeen weather station also calculates evapotranspiration using the 1982 Kimberly-Pennman equation (Penman 1948, Penman 1956, Wright 1982, Norihiro *et al.* 2002). Specifications for all data measurements at this station are given in Table 1. For the comparison of the *in situ* weather data and the Aberdeen weather data, we used a sampling period of 100 days beginning on 14-June-2006.

SOGS Data and Imagery

SOGS raster layers (1000m x 1000m pixels) were acquired through the Numerical Terradynamic Simulation Group (NTSG) at the University of Montana. The acquisition included daily predictions of temperature, precipitation, dew point, and solar radiation models derived from the SOGS algorithms. Each of these raster layers was delivered in Universal Transverse Mercator (UTM) NAD 83 projection and datum. All analyses were completed in the 'as-delivered' format using the values from the pixel containing the weather station's location.

Data Analysis

The location (point vector data) of the *in situ* weather station and Aberdeen weather station were projected into UTM NAD 83 using ESRIs ArcGIS 9.2 to match the geographic reference system used by the SOGS raster layers. Daily minimum, maximum, and average temperatures, daily total precipitation, and daily total solar energy were calculated from the two-hour recordings made by the Davis Vantage Pro2 weather sensor at the O'Neal Ecological Reserve using the ArcGIS 9.2 summarize function. The SOGS algorithm for solar radiation is an expression of solar energy in MegaJoules per square meter per day ($MJ/m^2/day$). To better compare solar energy values, the Davis Vantage Pro2 weather station data (recorded in Langleys (Ly) and calculated as Ly/day) was converted to $MJ/m^2/day$ using 1 Ly/day = 0.0419 $MJ/m^2/day$ (Ward and Trimble 2004). To compare the observed *in situ* weather data with the predicted SOGS data, corresponding SOGS pixel values (n = 100, 14-June-2006 through 21-September-2006) were extracted using the ArcGIS 9.2 data extraction tool (sample). This routine was completed for the six meteorological variables of interest: daily minimum temperature, daily maximum temperature, daily average temperature, precipitation, dew point, and solar radiation. The extracted data were saved to database tables and then imported into SPSS 14.0 for statistical analysis.

We first compared the observed *in situ* values of the six meteorological variables (daily minimum temperature, daily maximum temperature, daily average temperature, precipitation, dew point, and solar radiation) with the SOGS-predicted values to determine the accuracy of the SOGS meteorological data at a local scale. We built a linear regression model for each of the six variables of interest. The observed *in situ* values (n=100) for each variable were the response variables, while the SOGS-predicted values were the predictor variables.

We then compared the observed *in situ* values of daily minimum, maximum, and average temperatures, and precipitation with the observed weather data at the Aberdeen weather station. We again built a separate linear regression model for each of the four meteorological variables of interest. The observed values at the *in situ* weather station (*n*=100) for each variable were the response variables, while the observed values at the Aberdeen weather station were the predictor variables for each model. The objective of this modeling exercise was to determine if the meteorological data from a nearby station was more or less accurate than the SOGS-predicted data. To compare the predictive accuracies and to inform preferences between SOGS meteorological data and the nearby weather station data, we compared the mean squared deviation (MSD; the sum of squared deviations between predicted and observed values, divided by the number of observations) in addition to the coefficient of determination (R^2 or the proportion of variability explained by the model) of each model. MSD has been suggested to be more informative in model comparisons and model evaluations than coefficient of determination (Freund and Simon 1991, Gauch *et al.* 2003).

RESULTS

When the observed *in situ* values were examined with the SOGS-predicted values, average daily temperature had the highest coefficient of determination (0.93) and the SOGS values were a significant predictor variable (Table 2). Dew point, daily maximum temperature, and precipitation had the next highest coefficients of determination and the SOGS-generated estimates were all statistically significant as predictor variables (Table 2). SOGS daily minimum temperature was also a statistically significant predictor variable, but had a lower coefficient of determination of 0.79 compared to these variables. Solar energy had a low coefficient of determination of 0.24, although it was a significant predictor variable.

Table 2. Results of linear regression analysis ($P < 0.0001$) between *in situ* weather conditions (O'Neal Ecological Reserve, Idaho, USA), predicted SOGS values (*n* = 100), and the Aberdeen weather station, Idaho USA (*n* = 196).

	O'Neal Ecological Reserve and SOGS		**O'Neal Ecological Reserve and Aberdeen Weather Station**	
Weather variable	**Coefficient of determination (R^2)**	**Mean Squared Deviation (MSD)**	**Coefficient of determination (R^2)**	**Mean Squared Deviation (MSD)**
Minimum temperature	0.79	3.42	0.96	2.62
Maximum temperature	0.87	3.62	0.98	2.69
Average temperature	0.93	1.42	0.98	1.76
Precipitation	0.83	0.87	0.33	4.72
Dew point	0.90	1.49	---	---
Solar energy	0.24	20.37	---	---

When the observed *in situ* values were compared to the weather data from a nearby weather station, all predictor variables were also statistically significant (Table 2). Minimum, maximum, and average daily temperatures had high coefficients of determination of 0.96, 0.98, and 0.98, respectively. However, precipitation had an adjusted R^2 of only 0.33, although it was statistically significant (Table 2). Compared to the SOGS-predicted average temperature values, the Aberdeen weather station daily average temperature had greater correlation with the observed daily average temperature values at the O'Neal *in situ* weather station (R^2 of 0.98 versus 0.93). However, the SOGS-predicted daily average temperature produced a lower MSD compared to the Aberdeen weather station daily average temperature (1.76 versus 1.42). Daily minimum and maximum temperatures at the Aberdeen weather station also had greater correlation, compared to the SOGS-predicted values, with the observed *in situ* values. Aberdeen weather station daily minimum and maximum temperatures also produced lower MSD compared to the SOGS-predicted values, indicating that the regression models with Aberdeen weather station data performed better than the SOGS-based models (Table 2). In contrast with the temperature variables, the SOGS-predicted precipitation values had much greater correlation, compared to the Aberdeen weather station precipitation values, with the observed *in situ* precipitation values. The SOGS-based regression model of precipitation predictions also produced much lower MSD compared to the Aberdeen weather station precipitation predictions (Table 2) indicating that SOGS precipitation prediction performed much better than the nearby station data.

DISCUSSION

Our results indicate that SOGS predictions of daily average, maximum, and minimum temperature, dew point, and precipitation performed well at a local scale. While the SOGS predictions of solar energy did not perform well at a local scale, the low coefficient of determination was not surprising. The SOGS algorithm models solar energy as incident shortwave radiation (100-2000nm) and these data are not sensor-derived (Zhang *et al.* 2004). Rather, the solar energy model represents a derived surface-meteorological variable which is required for several MODIS algorithms such as gross primary productivity. As there generally are no daily measured solar radiation data from standard weather stations, the SOGS solar energy model is semi-empirically derived using elevation, latitude, and several spatially-interpolated environmental variables including the range of daily diurnal temperature, humidity, and precipitation (Thornton and Running 1999, Jolly *et al.* 2005).

Data from the *in situ* weather station, the Aberdeen weather station, and SOGS dataset are given in Figure 2 for comparison. Most of the graphs exhibit very similar curves illustrating the high correlations calculated in these analyses with the solar energy curves perhaps being the most interesting (Figure 2b). An offset was observed between weather values during the first two weeks in which the *in situ* weather station was in operation (13-June to 3-July). This offset may be explained as the new solar radiation sensor requires a break-in period before it functioned correctly. After the initial break-in period, the correlation between the datasets was much improved (R^2=0.56). Temperature curves were very similar for all three datasets (Figure 2d-f) as well as the dew point curves for the *in situ* weather station and SOGS dataset (Figure 2a)(note: dewpoint was not reported for the Aberdeen weather station). Figure 2c illustrates a better correlation between *in situ* weather station precipitation data and SOGS precipitation data compared to the correlation between *in situ* weather station precipitation data and the Aberdeen weather station precipitation data. The relationship curves reveal relatively good correspondence for the date when the precipitation events occurred but a low correspondence in the quantity of precipitation recorded for each event. This suggests that the weather stations were in close enough proximity to receive rainfall from the same weather events, but the differences in terrain may have caused differences in the actual amount of precipitation received.

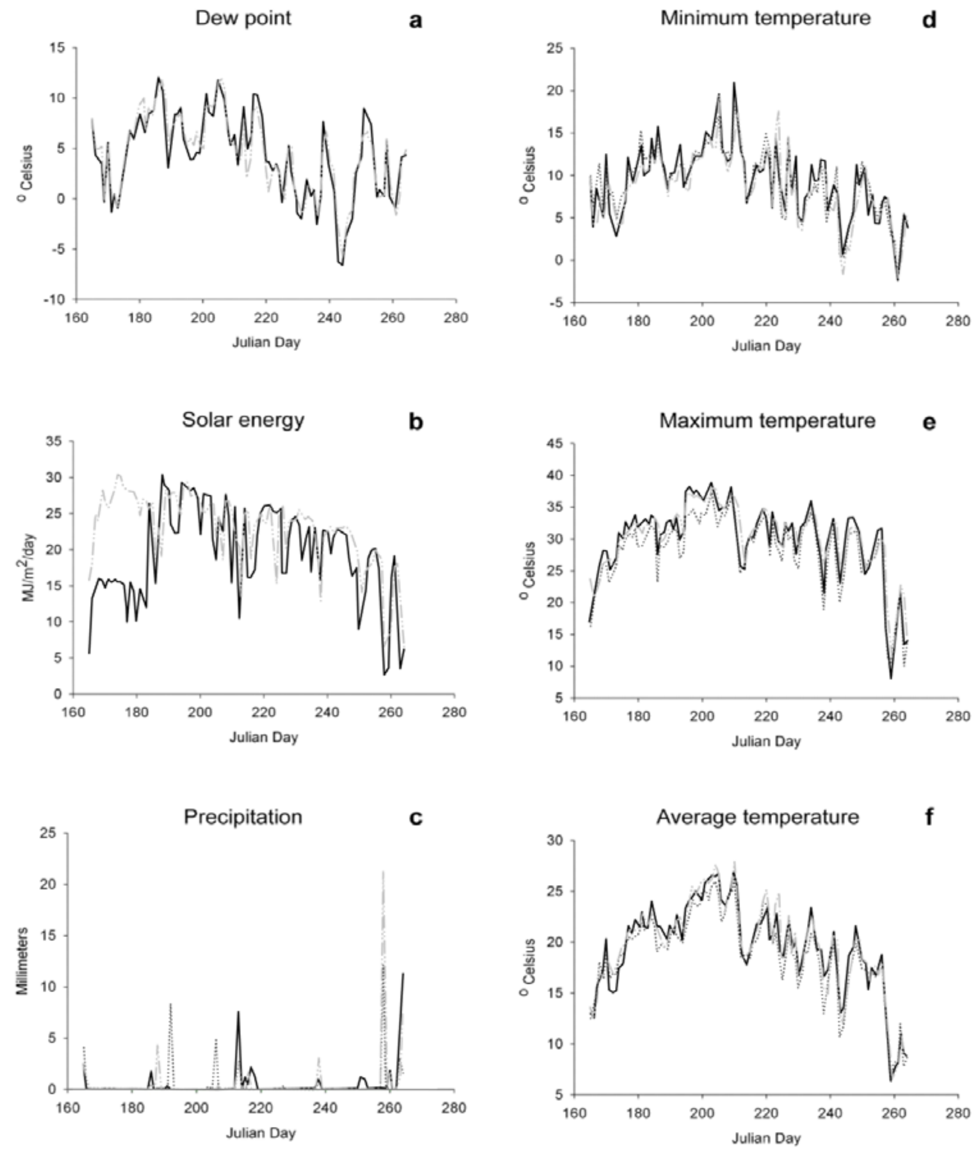

Figure 2. Temporal comparison between weather variables from the O'Neal Ecological Reserve (Idaho, USA) *in situ* weather station (solid black line), the predicted SOGS data (dashed grey line), and the nearby weather station in Aberdeen, Idaho (USA) (dotted grey line). Dew point and solar energy data were not available for the Aberdeen weather station and so are not shown in a or b.

Model comparisons indicate the Aberdeen weather station predictions of daily minimum and maximum temperatures were better than the SOGS predictions. These results suggest that site-specific, local-scale research at the O'Neal Ecological Reserve could use the daily minimum and maximum temperature measurements from the nearby weather station rather than the SOGS predictions. However, the SOGS predictions of precipitation at the O'Neal Ecological Reserve were far better than the precipitation predictions from the Aberdeen weather station data. This suggests that in the semi-arid rangelands of southeastern Idaho with variable terrain between the nearby weather station and research site, the SOGS prediction of precipitation should be used. This validation result of the SOGS precipitation prediction at a local scale is consistent with validation results of SOGS precipitation predictions for the broader-scale, continental United States (Jolly *et al.* 2005). Our regression models and model comparisons did not indicate a clear preference in daily average temperature predictions between the SOGS data and the nearby weather station data. It appears that both predictions had high correlation with the *in situ* measurements suggesting either prediction could be used. In general, it might seem that an *in situ* weather station is the better data source, but the authors suspect that for spatially-extensive study areas, data from a single weather station might introduce similar inaccuracies as demonstrated with the nearby weather station data used in this study. For this reason, there exists a need for a spatially-continuous and accurate weather dataset. The SOGS dataset provides one such source. In addition to the accuracy issues, the authors also note that the use of the SOGS dataset ensures a consistent data source.

The results presented in this paper indicate SOGS is an accurate spatially-continuous dataset well suited to modeling primary productivity at local scales. In addition, the SOGS dataset appears to offer great potential for climate change modeling. However, future studies should first validate the correspondence between these same weather parameters over increasingly larger areas before applying SOGS data to model climate change at continental scales.

CONCLUSIONS

This study examined the correlation between SOGS data and *in situ* weather observations and the correlation between a nearby weather station and *in situ* weather observations over the 2006 growing season at the O'Neal Ecological Reserve in southeastern Idaho. The results of this study indicate nearby weather station data has a slightly better correlation with *in situ* observations for most weather variables, while SOGS data has better correlations with *in situ* precipitation observations.

Modeling climate change and ecological processes frequently requires the use of weather data as a primary data input. The use of nearby weather stations may be acceptable in some cases, but the proximity of the nearby weather station to the study area and terrain characteristics between the weather station and study area might affect prediction accuracy especially those related to precipitation. In such cases, SOGS data could be used to improve results. The best solution to collect weather data input for modeling purposes might be the use of an *in situ* weather station, but for spatially extensive study areas, single point observations extrapolated over large areas will introduce the same inaccuracies as demonstrated with the nearby weather station used in this study. In contrast, the use of SOGS data ensures a consistency in source data that is spatially continuous.

Overall, the validation of the SOGS weather models closely agreed with the independent, *in situ* weather measurements. With these data, more accurate models of productivity and biomass are possible. In addition, the spatially-continuous SOGS data can fill an important niche in global climate change and environmental modeling efforts for local, regional, continental, and global scales providing accurate spatial and temporal weather data. However, further analysis is required to generalize these results over an entire year and across different spatial scales.

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Soil Moisture Modeling using Geostatistical Techniques at the O'Neal Ecological Reserve, Idaho

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ABSTRACT

Spatial interpolation techniques were used to model soil moisture patterns at the O'Neal Ecological Reserve in southeast Idaho and investigate interactive effects that may improve modeling results. The individual prediction models, created through ordinary kriging, were compared to a sequential Gaussian simulated prediction model(SGSIM). SGSIM always resulted in a lower magnitude of difference when compared to the ordinary kriging model. This may be due to the autocorrelation structure of each individual treatment which was more difficult to infer than for the entire dataset (in which SGSIM parameters were based upon). The degree of uncertainty in modeling the autocorrelation structure likely propagated through the prediction comparisons. SGSIM using 250 realizations proved most reliable in estimating the local soil moisture mean.

KEYWORDS: rangelands, GIS, kriging, sequential Gaussian simulated prediction model

INTRODUCTION

Rangeland condition varies with numerous parameters including grazing management practices. Ellison (1954) noted the impact of grazing on vegetation and soil is primarily realized through "alterations of soil moisture." In more recent years, Gill (2007) examined difference in soil processes, namely water content, between grazing treatments compared to an area with 90 years of exclusion from grazing. Thomas and Squires (1991) argue that soil moisture is the principal determinant of productivity and is the primary indicator of rangeland condition.

To determine the effect of various grazing treatments on soil moisture, we developed a controlled experiment at the ISU O'Neal Ecological Reserve (Figure 1). The study site was divided into three pastures each with a different grazing treatment applied—total rest, rest-rotation grazing, and adaptive grazing (simulated holistic planned grazing [SHPG]). This paper describes the development of a soil moisture model that allows for evaluation of soil moisture within and between treatments.

METHODS AND RESULTS

The data set used in this study consists of 145 stratified random sample points generated in ArcMap using the Hawth's Tools extension. The samples were stratified by pasture with an approximately equal number of sample points located in each treatment (n = 49 in the total rest treatment; n = 46 in rest-rotation grazing treatment; n = 50 in the adaptive grazing treatment pastures). Throughout July 2006, four soil moisture measurements were taken and averaged at each sample point using Campbell Scientific, Inc. HydroSense (http://www.campbellsci. com/cs620) hand-held probe (10 cm) with accuracy of +/-3.0 % volumetric water content (electrical conductivity of <2 dS m-1). These data were then entered into a geodatabase within ArcGIS for further analysis.

SPOT 5 satellite imagery (10 x 10 m resolution) was acquired during July 2006, coincident with the field sampling campaign. This imagery was used to derive normalized difference vegetation indices (NDVI) to help corroborate and support soil moisture analysis as NDVI is typically negatively correlated with soil moisture (Adegoke and Carleton 2002). To do this, a cross-correlation between soil moisture and NDVI can be applied which may help bias our interpolation of soil moisture in unsampled areas assuming that the information contained in NDVI can reduce the variance of the soil moisture estimation error (Isaaks and Srivastava 1989). Cross-correlation may also be employed where soil moisture measurements were undersampled as compared to the exhaustively sampled NDVI (where each pixel has a value specific to that location). The processes involved in cross-correlation are further explained through cokriging, discussed below.

Spatial interpolation techniques were used to produce a soil moisture map of the O'Neal Ecological Reserve. There are various types of spatial interpolation and estimation used in this study. Kriging is a group of geostatistical techniques to interpolate the value of a variable $Z(x)$ (e.g. soil moisture Z as a function of geographic location) at an unsampled location x_o by using sampled measurements $z_i = Z(x_i)$, i=1, …, n of the same variable at nearby locations $x_1, \dots, x_n$ (Issaks and Srivastava 1989). The spatial dependence is quantified in terms of a variogram gamma(x,y) and covariance function $c(x,y)$ of the variable. A variogram highlights the variance of a variable as a function of a specified geographic distance between measurements. This specified distance is called a lag. Kriging is known as a smoothing interpolator because real world differences between high value and low value areas become smooth, possibly hiding "real" sudden changes. Ordinary kriging and cokriging were two kriging methods used in this study. Ordinary kriging is defined with the acronym BLUE for "best linear unbiased estimator." The term "best" is used because the algorithm minimizes the variance of the errors (Isaaks and Srivastava 1989); "linear" is used because kriging estimates are weighted linear combinations of the available data; and it is considered "unbiased" as the algorithm attempts to set m_R, (the mean residual or error) equal to 0. In comparision, cokriging is a spatial interpolation method that "minimizes the variance of the estimation error by exploiting cross-correlation between several variables" (Issaks and Srivastava 1989).

In addition to the above kriging methods, sequential Gaussian simulation was also used in this study. Sequential Gaussian simulation differs from kriging in that stochastic realizations are generated that honor global statistics as quantified by not only the variogram but also the histogram of the data. One can never expect kriging to reproduce the correct spatial association (global statistics) of the data in question (as measured by the variogram) because of the smoothing effect of kriging and for this reason sequential Gaussian simulation is sometimes preferred. However, to better ensure the correct geographical global statistics are applied, the user needs to define the joint probability model of properties at all grid locations taken together, not one-by-one as done in kriging. Sequential Gaussian simulation helps to overcome the smoothing effect of kriging and generates stochastic realizations that honor a specific geographic pattern as quantified by the variogram and histogram. Estimates are not only based on the variogram but also through the generation of a stochastic (random) sample from the joint probability distribution (Deutsch and Journel 1992).

The steps used to produce the model were as follows:

1. Ordinary kriging using the entire soil moisture dataset.
2. Co-kriging with NDVI.
3. Sequential Gaussian Simulation.

Exploratory Data Analysis

All data were statistically analyzed to determine distribution, relationship, and trend. Summary statistics of each grazing treatment are given in Table 1. To evaluate differences between mean percent soil moisture of each grazing treatment, we used a paired t-test. The results demonstrate differences in mean values between treatments in all cases (P = 0.05).

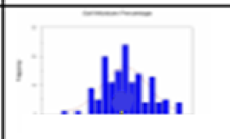
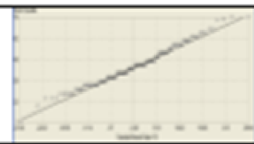
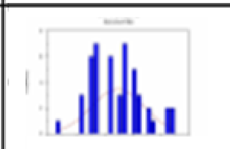
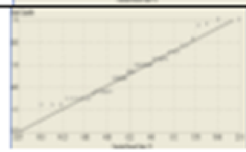
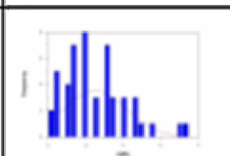
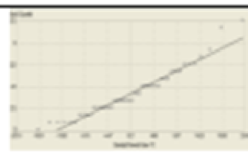
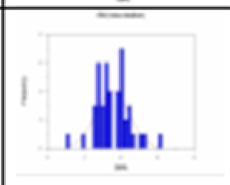
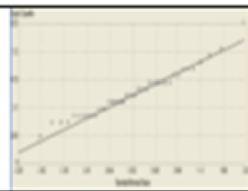
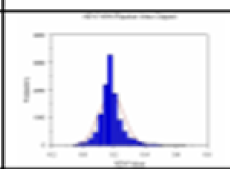
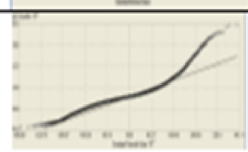
Table 1. Volumetric water content (%) of soil in each individual treatment (samples taken in July, 2006).

	Total Rest	**Adaptive**	**Rest-Rotation**
Mean	4.25	5.47	3.54
SD	0.8370	0.9396	0.9212
SEM	0.1196	0.1389	0.1356
n	49	44	48

Note: The soil moisture dataset (n =141 points) had a mean percent volumetric water content of 4.44 with a standard deviation of 1.19.

Each dataset was evaluated to describe its distribution and normality using the Kolmogorov-Smirnov Test (Table 2). The results indicate that each soil moisture dataset was normally distributed while the NDVI dataset was not normally distributed.

Table 2. Normality summary of each dataset used in this project. Each soil moisture dataset was found to be normally distributed within a 95 % confidence interval. The NDVI dataset was not normally distributed within 95 % confidence.

	Histogram	Normal QQ Plot	K-S p-value	Ho: Dataset is normally distributed
SM% Entire Dataset			0.1839	Accept
SM% Adaptive (SHPG)			0.3493	Accept
SM% Total Rest			0.2145	Accept
SM% Rest-Rotation			0.7029	Accept
NDVI			0.0000	Reject

Note: SM% = soil moisture percent or percent volumetric water content.

Next, trend was examined using the trend tool in ArcGIS 9.1 Geostatistical Analyst. Results suggest no strong regional trend within dataset. However, the trend tool was useful in noting that several of the highest soil moisture values were located in the adaptive grazing pasture.

The semivariogram cloud for the entire soil moisture dataset revealed that no single data point was responsible for the large squared differences observed. Also, a "transition zone" was identified and the majority of the large squared-differences (at the smaller lags) were found within the adaptive/SHPG grazing pasture (Figure 1).

The semivariogram cloud was analyzed by treatment, and the sample points with the largest squared differences at the smaller lag spacings were highlighted. These points were found nearest the boundary of each treatment and particularly near the adaptive pasture boundaries (Figure 2).

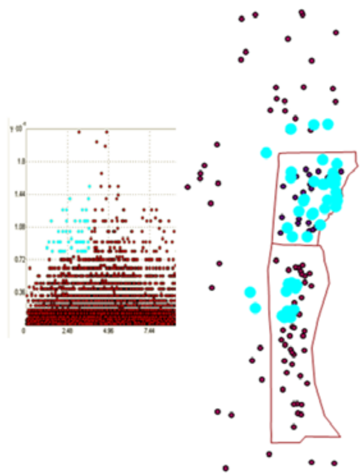


Figure 1. Most of the large squared differences at the smaller lag spacings (transition zone) were linked to sample points in the simulated holistic planned grazing pasture (see the highlighted points in blue).

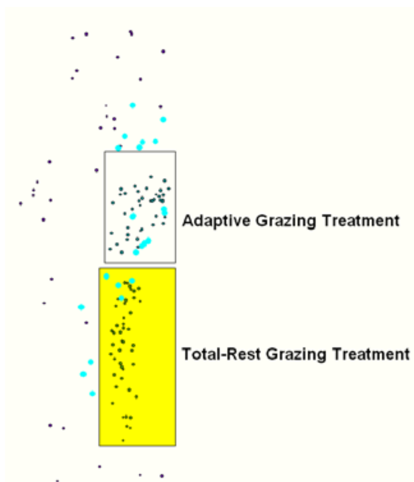


Figure 2. Semivariogram clouds of each grazing treament were used to highlight the points with the largest squared differences in the transition zone. It is apparent that most of the difference occurs along the edges of each treatment near the fences.

Variography

The sill is the semivariance value at which the variogram levels off. The sill is also used to refer to as the "amplitude" of a certain component of the semivariogram. Refrerring to figure 3, "sill" could refer to the overall sill (1.0) *or* to the difference (0.8) between the overall sill and the nugget (0.2); the interpretation depends upon the context. The range is the lag distance at which the semivariogram (or semivariogram component) reaches the sill value. Presumably, autocorrelation is effectively zero beyond the range. In variography, the definition of major and minor range is important in capturing spatial autocorrelation. In theory, the semivariogram value at the origin (0 lag) should be zero. If the semivariogram value is significantly different from zero at or near the origin, the semivariogram value is referred to as the "nugget". The nugget represents variability at distances smaller than the typical sample spacing; including measurement error (Isaaks and Srivastava 1989).

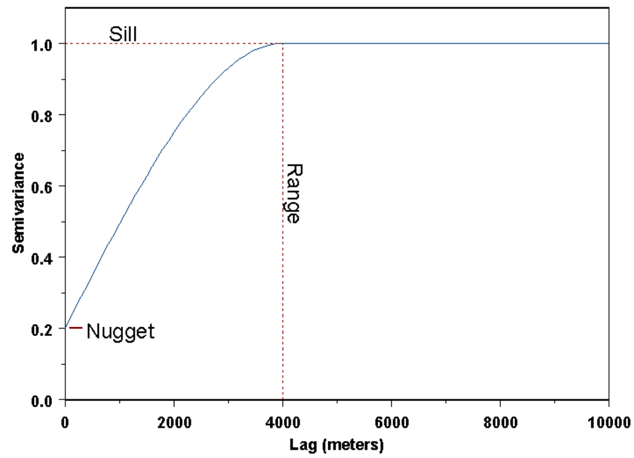


Figure 3. Semivariogram showing the individual components of a semivariogram.

Each of the components discussed above are important parts of variography. Variography was performed on the entire dataset as well as on each individual grazing treatment dataset. The autocorrelation structure of the entire dataset was fairly easy to infer, but each treatment, when separated, became more difficult to infer its autocorrelation structure. To accomplish this empirically, VarioWin software (http://www-sst.unil.ch/research/variowin/index.html) was used. The information produced within VarioWin was then applied in the ArcGIS Geostatistical Analyst.

To make sure that the "hump" (at a lag distance of ~560 meters; Figure 4) in the entire soil moisture dataset was not a trend that required "detrending", an omnidirectional semivariogram was produced in ArcGIS Geostatistical Analyst with 1st order trend removal to visualize the affect on the autocorrelation structure.

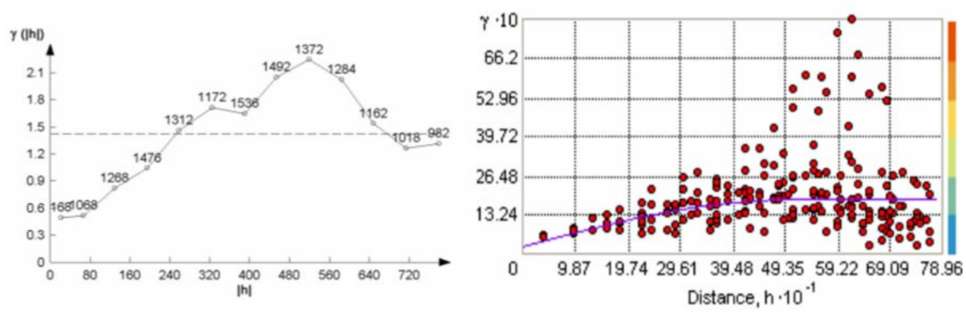


Figure 4. This is an omnidirectional semivariogram of the entire soil moisture dataset. In all cases, variography was corroborated between Geostatistical Analyst and VarioWin.

One requirement of kriging is that the data must not have regional/geographic trends which can skew interpolation estimates unfavorably. If trends are detected, detrending can be to prepare the data for subsequent kriging procedures. If the autocorrelation structures of an omnidirectional semivariogram change significantly with 1st order trend removal then there is a need for detrending. In this case, the difference was negligible and it was decided that the soil moisture variable did not require detrending.

In all cases, a nugget was applied and a nested model structure defined to better delineate the short-range spatial autocorrelation structure. Major and minor ranges were specified to better capture and represent spatial autocorrelation within and between model structures. The final model parameters, semivariogram, and covariance estimators for each soil moisture dataset are outlined below and in Figures 5-8.

Variable- Soil Moisture (entire dataset)
Lag Size: 65 Number of Lags: 12 Angular Tolerance: 30 Bandwidth: 3.0
Nugget: 0.05

Model 1- Manual Fit
Model Type: Exponential
Major Range: 50 Minor Range: 50 Direction: -
Partial Sill: 0.30

Model 2- Auto-Fit
Model Type: Spherical
Major Range: 770.5 Minor Range: 428 Direction: 63.6
Partial Sill: 1.46

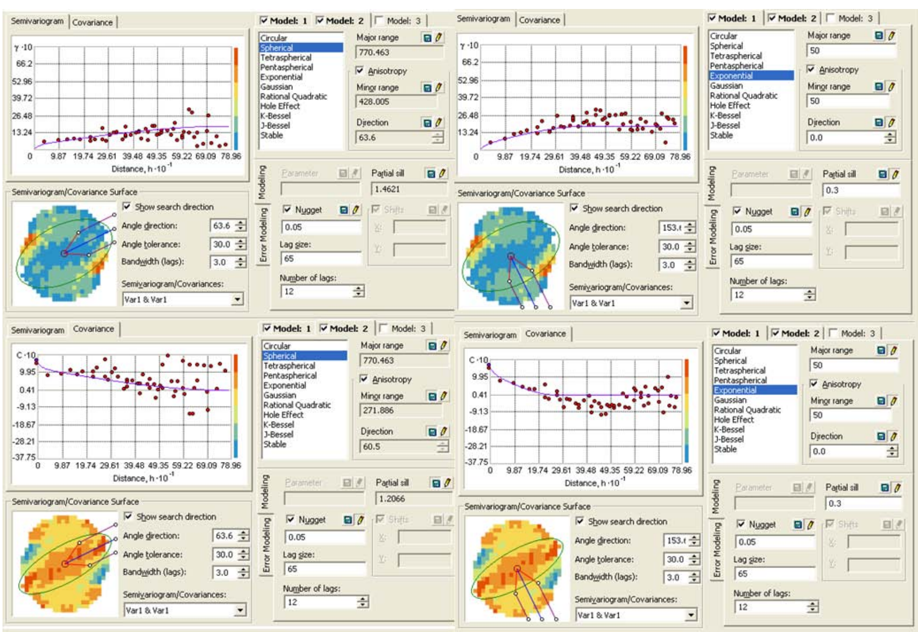


Figure 5. Variography parameters, semivariogram estimators, and covariance estimators of the entire soil moisture dataset. Each estimator is displayed with major range (left column) and minor range (right column).

Variable- Soil Moisture (adaptive treatment [SHPG])
Lag Size: 21 Number of Lags: 15 Angular Tolerance: 30 Bandwidth 3.0
Nugget: 0.20

Model 1- Manual Fit Model Type: Exponential Major Range: 50 Minor Range: 50
Direction:-

Partial Sill: 0.40

Model 2- Auto Fit Model Type: Spherical Major Range: 315 Minor Range: 212
Direction: 66
Partial Sill: 0.42

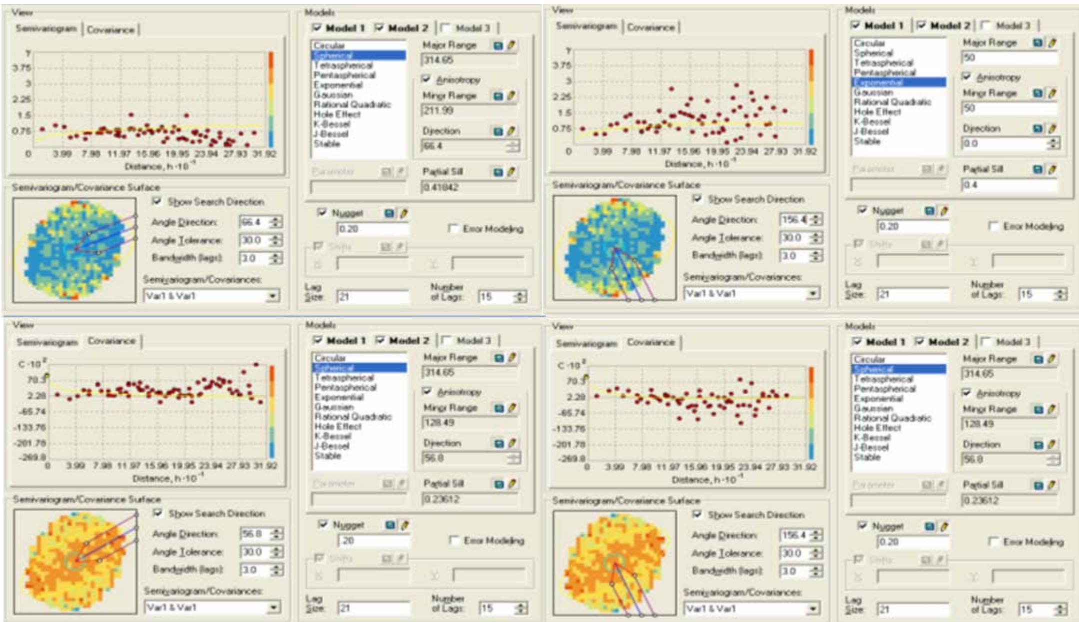


Figure 6. Variography parameters, semivariogram estimators, and covariance estimators of the adaptive grazing treatment soil moisture dataset. Each estimator is displayed in terms of major range (left column) and minor range (right column).

Variable- Soil Moisture in Total Rest Treatment:
Lag Size: 18 Number of Lags: 12 Angular Tolerance: 30 Bandwidth 3.0
Nugget: 0.05

Model 1- Manual Fit Model Type: Sperical Major Range: 50 Minor Range: 50
Direction:-
Partial Sill: 0.15

Model 2- Auto Fit Model Type: Spherical Major Range: 213 Minor Range: 197
Direction: 37
Partial Sill: 0.27

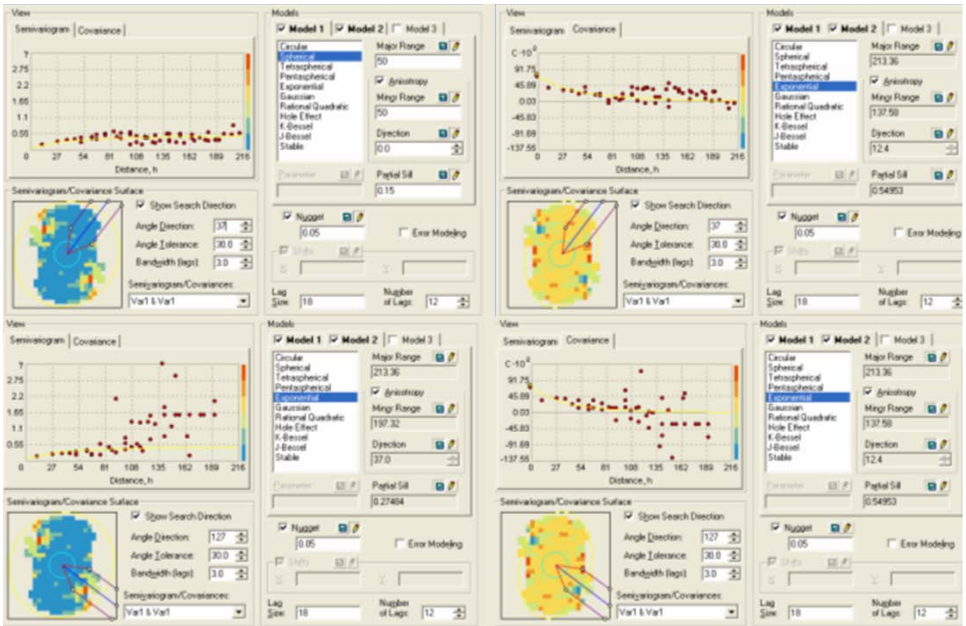


Figure 7. Variography parameters, semivariogram estimators, and covariance estimators of the total rest grazing treatment soil moisture dataset. Each estimator is displayed in terms of major range (left column) and minor range (right column).

Variable- Soil Moisture in Rest Rotation Treatment:
Lag Size: 85 Number of Lags: 15 Angular Tolerance: 30 Bandwidth 3.0
Nugget: 0.05

Model 1- Manual Fit Model Type: Exponential Major Range: 80 Minor Range: 80
Direction:-
Partial Sill: 0.35

Model 2- Auto Fit Model Type: Exponential Major Range: 1274 Minor Range: 634
Direction: 38
Partial Sill: 0.42

Ordinary Kriging of Soil Moisture

The models that best captured the soil moisture autocorrelation structure used short-range autocorrelation (nested transitive structure) with a small nugget (< 0.20). Both short-range and long-range variance anisotropy (the property of being directionally dependent, as opposed to isotropy, which means homogeneity of value expressed in all directions) was absent as determined by finding the quotient of the maximum range divided by the minimum range. Where anisotropy is present, the resulting value will be < 2.0 (Isaaks and Srivastava 1989). In addition, because no indication of pronounced geometric anisotropy was revealed in any of the models, a constrained circular search area was used for kriging (Isaaks and Srivastava 1989).

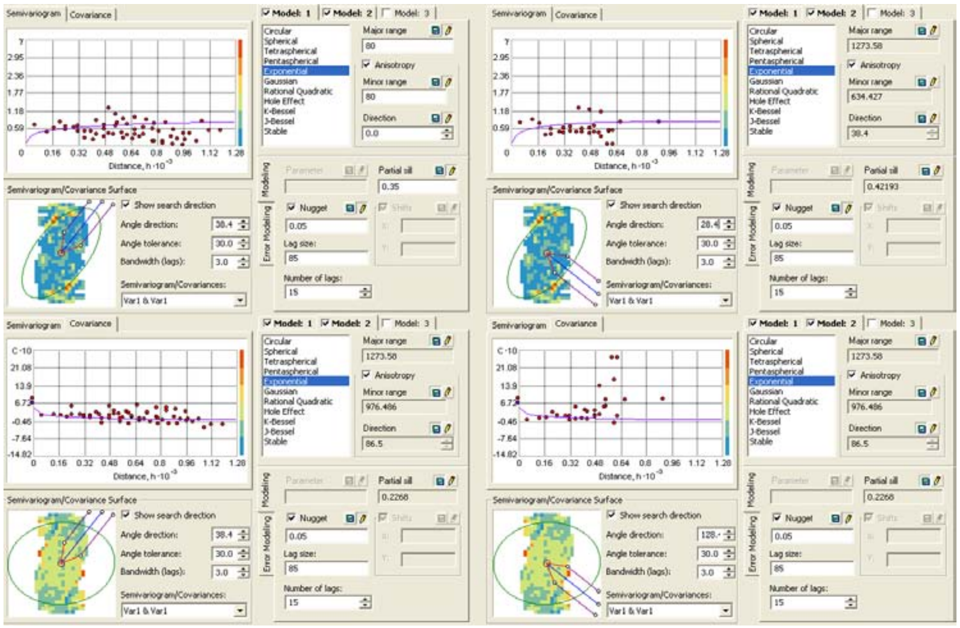


Figure 8. Variography parameters, semivariogram estimators, and covariance estimators of the rest-rotation grazing treatment soil moisture dataset. Each estimator is displayed in terms of major range (left column) and minor range (right column).

Since each of the variogram nuggets were small relative to the sill heights, a lower number of neighbors was specified in all cases because of the relative importance of the nugget compared to the sill (i.e., to help ensure that the closest neighboring samples were given the significant weight). The final kriging search strategies are summarized below and the prediction maps and standard error maps of each model are presented in Figures 9-12.

Entire Soil Moisture Dataset Search Strategy:

- Neighbors to Include: 15
  - Used 15 neighbors because the nugget is small relative to the sill and I want to ensure that the closest neighboring samples are given the significant weights.
- Include at Least: Not Checked
  - Do not want to "force" predictions where the data is lacking.
- Shape type: 4-Sectored (N-S)
  - Sampling regime consisted of measuring in same orientation
- Shape Major/Minor Semiaxes: 150/150
  - There was not pronounced geometric anisotropy so a circular search area of 150 is used.
  - Wanted a limited search that is constrained by the autocorrelation short-range variance component.

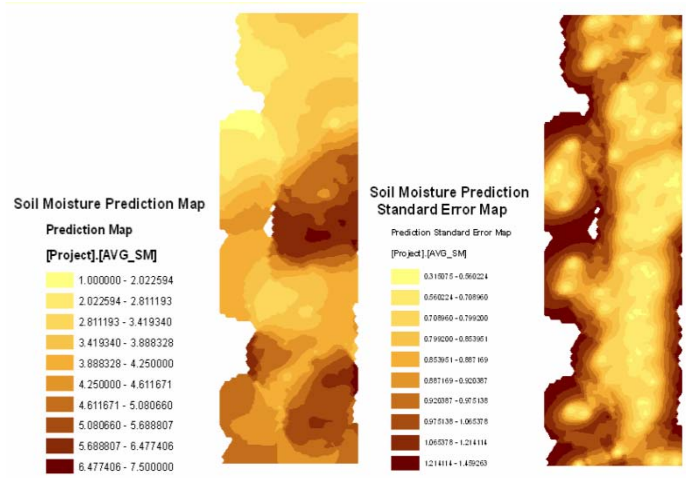


Figure 9. Ordinary kriging prediction pap (left) and standard error map (right) of the entire soil moisture dataset.

Adaptive Grazing (SHPG) Treatment Search Strategy:

- Neighbors to Include: 12
  - Used 12 neighbors because the nugget is small relative to the sill and I want to ensure that the closest neighboring samples are given the significant weights.
- Include at Least: Not Checked
  - Do not want to “force” predictions where the data is lacking.
- Shape type: 4-Sectored (N-S)
  - Sampling regime consisted of measuring in same orientation
- Shape Major/Minor Semiaxes: 100/100
  - There was not pronounced geometric anisotropy so a circular search area of 100 is used.
  - Wanted a limited search that is constrained by the autocorrelation short-range variance component.

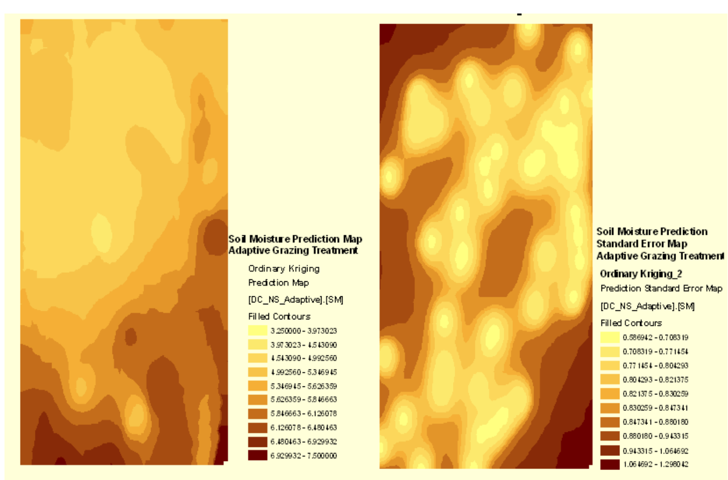


Figure 10. Ordinary kriging prediction pap (left) and standard error map (right) of the adaptive grazing treatment soil moisture dataset.

Total Rest Grazing Treatment Search Strategy:

- Neighbors to Include: 10
- Include at Least: Not Checked
  - Do not want to "force" predictions where the data is lacking.
- Shape type: 4-Sectored (N-S)
  - Sampling regime consisted of measuring in same orientation
- Shape Major/Minor Semiaxes: 100/100
  - There was not pronounced geometric anisotropy so a circular search area of 100 is used.
  - Wanted a limited search that is constrained by the autocorrelation short-range variance component.

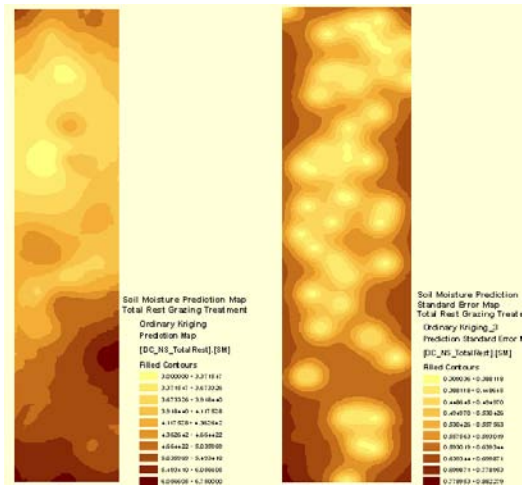


Figure 11. Ordinary kriging prediction pap (left) and standard error map (right) of the total rest treatment soil moisture dataset.

Rest-Rotation Grazing Treatment Search Strategy:

- Neighbors to Include: 16
- Include at Least: Not Checked
  - Do not want to "force" predictions where the data is lacking.
- Shape type: 4-Sectored (N-S)
  - Sampling regime consisted of measuring in same orientation
- Shape Major/Minor Semiaxes: 150/150
  - There was not pronounced geometric anisotropy so a circular search area of 150 is used.
  - Wanted a limited search that is constrained by the autocorrelation short-range variance component.

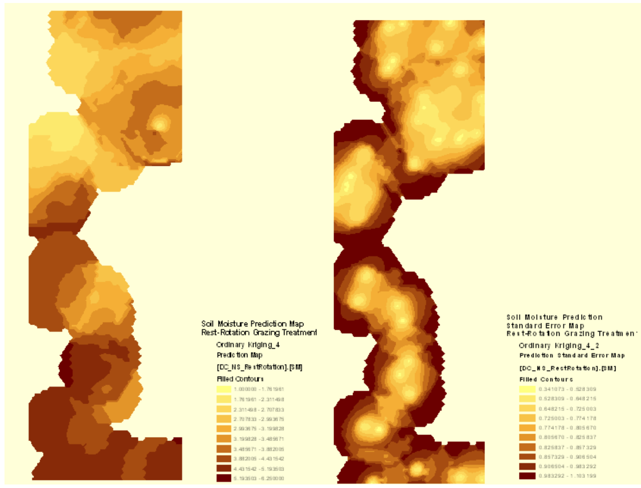


Figure 12. Ordinary kriging prediction pap (left) and standard error map (right) of the rest-rotation grazing treatment soil moisture dataset.

Cross validation statistics of each of the above models and their respective search strategies are given in Table 3. It should be noted that strict comparisons of these cross-validation statistics are not valid because although each treatment had a similar search strategy, each treatment area had its own unique autocorrelation model.

Table 3. Ordinary kriging cross-validation statistics for each grazing treatment. Note how each statistics performance is evaluated in the far right column.

	Entire	Adaptive	Total Rest	Rest-Rotation	How error statistic is evaluated
Mean Estimation Error	-0.00793	-0.02425	-0.06875	0.02811	Close to 0
Mean Standardized Error	-0.003888	-0.02248	-0.07841	0.02477	Close to 0
Root-Mean-Square Estimation Error	0.8259	0.8649	0.6095	1.007	Small as possible
Error Regression Slope	0.665	0.249	0.458	0.175	Close to 1
Average Standard Error	0.7682	0.8264	0.5569	0.8201	Small as possible
Root-Mean-Square Standardized Error	1.134	1.079	1.007	1.306	Close to 1
Ratio of Root-Mean-Square/Average Standard Error	1.075	1.047	1.094	1.228	Close to 1

Cokriging of Soil Moisture with NDVI

The ability to improve the final soil moisture model by applying cokriging using NDVI was evaluated. Correlation between NDVI and each soil moisture dataset was determined using Pearson Correlation Coefficient (r). Results indicate that only the entire soil moisture dataset and the adaptive grazing soil moisture dataset bore any meaningful correlation with NDVI ($p=0.05$) (Table 4). Based upon this information, cokriging was performed for the entire soil moisture dataset and the adaptive grazing soil moisture dataset. However, it should be noted that although there were apparent significant correlations between these datasets, the fit to the regression line was poor.

Table 4. Correlation statistics and hypothesis testing of the correlation between NDVI and soil moisture datasets.

	Pearson Correlation Coefficient (r)	tcrit	t	Ho: r=0 (95% CI)
Entire Dataset	-0.2045	1.979	2.4627	Reject
Adaptive	-0.3360	2.0147	2.419	Reject
Total Rest	-0.0340	2.0137	0.232	Do not reject
Rest Rotation	-0.2395	2.0189	1.599	Do not reject

Variography was conducted using the NDVI dataset following the same protocols detailed above. The NDVI dataset autocorrelation structure was fairly easy to infer. This was expected given the amount of data available and the inherent spatial autocorrelation which exists within remotely sensed data. The final model parameters, semivariogram, and covariance estimators are summarized below and presented in Figure 13.

Variable- NDVI Exhaustive Dataset:
Lag Size: 35 Number of Lags: 16 Angular Tolerance: 30 Bandwidth: 3.0
Nugget: 0.0012

Model 1- Manual Fit
Model Type: Exponential
Major Range: 100 Minor Range: 100 Direction: -
Partial Sill: 0.0030

Model 2- Auto-Fit
Model Type: Spherical
Major Range: 558 Minor Range: 152 Direction: 9.2
Partial Sill: 0.0023

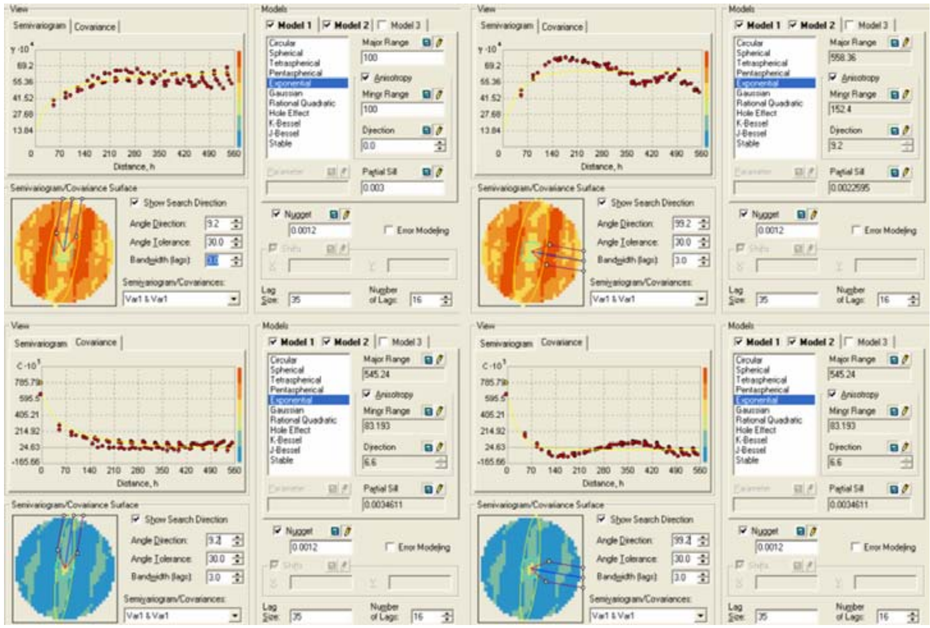


Figure 13. Variography of NDVI exhaustive dataset.

Cross-variography was performed on both the entire soil moisture dataset and the adaptive treatment dataset (with NDVI) using ArcGIS Geostatistical Analyst. Cross-variography is different from variography in that cross-variography is the process of modeling spatial autocorrelation of correlated variables (Issaks and Srivastava 1989). The best cross-covariance model parameters and cokriging strategy are summarized below.

Cross-Variography Using Entire Soil Moisture Dataset (Primary Variable) and NDVI:
Lag Size: 15 Number of Lags: 15 Angular Tolerance: 30 Bandwidth: 3.0

Cov(SM-SM)
Model 1 Model Type: Exponential
Major Range: 50 Minor Range: 50 Direction: -
Partial Sill: 2.30
Model 2 Model Type: Exponential
Major Range: 338 Minor Range: 139 Direction: 13
Partial Sill: 1.06 Nugget: 0

Cov(SM-NDVI)
Model 1 Model Type: Exponential
Major Range: 50 Minor Range: 50 Direction: -
Partial Sill: 0.0056
Model 2 Model Type: Exponential
Major Range: 338 Minor Range: 139 Direction: 13
Partial Sill: 0.0032 Nugget: 0

Cov(NDVI-NDVI)
Model 1 Model Type: Exponential
Major Range: 50 Minor Range: 50 Direction: -
Partial Sill: 0.1133
Model 2 Model Type: Exponential
Major Range: 338 Minor Range: 139 Direction: 13
Partial Sill: -0.0183

Cokriging of Entire Dataset Search Strategy:

- Neighbors to Include: 18
- Include at Least: Not Checked
  - Do not want to "force" predictions where the data is lacking.
- Shape type: 4-Sectored (N-S)
  - Sampling regime consisted of measuring in same orientation
- Shape Major/Minor Semiaxes: 150/150
  - There was not pronounced geometric anisotropy so a circular search area of 150 is used.
  - Wanted a limited search that is constrained by the autocorrelation short-range variance component.

Given that cokriging was evaluated as a way to improve soil moisture prediction, cross-validation statistics were compared between cokriging with NDVI and ordinary kriging. The results, shown in Table 5, indicate that from a strict comparison of cross-validation statistics, ordinary kriging performed better in all cases as compared to cokriging with NDVI.

Table 5. Comparison of ordinary kriging of the entire soil moisture dataset and cokriging of the entire dataset with NDVI. The far-right column defines how each cross-validation statistic was evaluated. In all cases ordinary kriging performed better than cokriging (indicated by the *).

	Ordinary Kriging	Cokriging	How error statistic is evaluated
Mean Estimation Error	-0.00793	0.0164	Close to 0
Mean Standardized Error	-0.003888	0.01062	Close to 0
Root-Mean-Square Estimation Error	0.8259	0.8977	Small as possible
Error Regression Slope	0.665	0.633	Close to 1
Average Standard Error	0.7682	1.454	Small as possible
Root-Mean-Square Standardized Error	1.134	0.675	Close to 1
Ratio of Root-Mean-Square/Average Standard Error	1.075	0.617	Close to 1

Finding any cross-autocorrelation structure within the adaptive treatment dataset proved practically impossible. However, cokriging was still performed on the dataset and compared to ordinary kriging of the same adaptive grazing dataset. When the two predictive models were compared in ArcMap by calculating the difference between the ordinary kriging raster layer less the cokriging raster layer (using raster calculator), the magnitude of differences was determined to be unacceptable. The maximum difference was 1.71 which is ~32 % of the mean soil moisture value for the adaptive grazing pasture study area) (Figure 14).

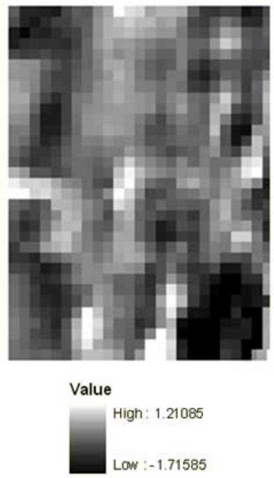


Figure 16. Difference between the ordinary kriging-derived model and the cokriging-derived model (using NDVI) within the adaptive grazing (SHPG) treatment area. Notice the large magnitude of difference. The maximum difference is ~32 % of the mean soil moisture value of the adaptive treatment.

Sequential Gaussian Simulation of Soil Moisture (SGSIM)

Sequential Gaussian simulation (SGSIM) was explored as a way to model soil moisture spatial variability using GSLIB Geostatistical Software Libray (http://www.gslib.com/). Since SGSIM requires data to exhibit multivariate Gaussian behavior (Deutsch and Journel 1992), this behavior was tested (Figure 15), with results indicating reasonable correspondence between at least 3 of the 4 indicator semivariograms ($p=0.02$, $p=0.06$, and $p=0.08$). The soil moisture dataset was considered to exhibit multivariate Gaussian behavior and SGSIM was used.

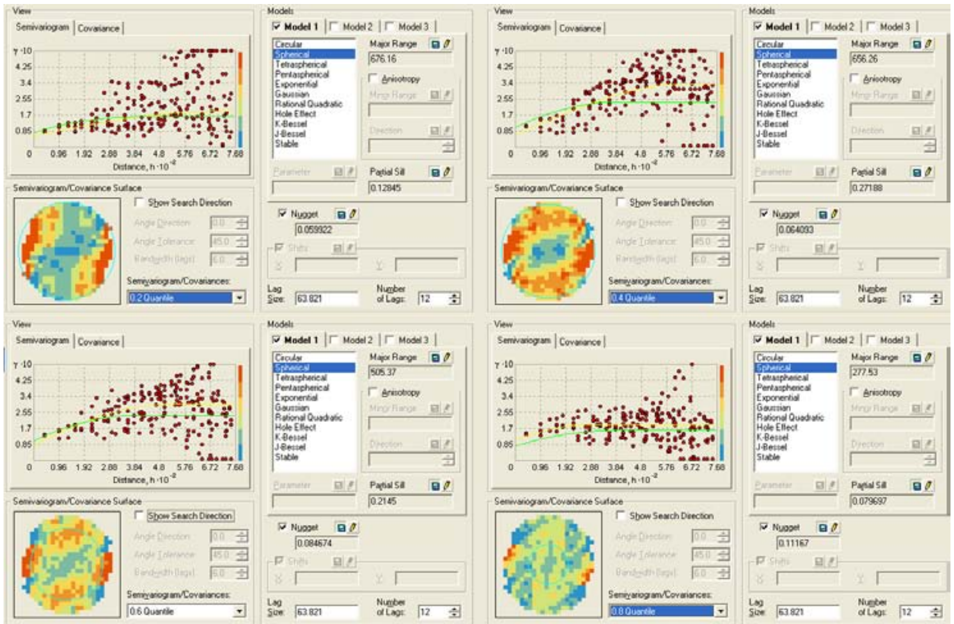


Figure 15. Starting at the upper left image and continuing clockwise: p=0.02 threshold, p=0.04 threshold, p=0.06 threshold, and p=0.08 threshold. Notice the reasonable correspondence with the indicator semivariograms (green line).

Since SGSIM requires variogram modeling in "normal-scored space" (Deutsch and Journel 1992), the best model to apply to the entire study area dataset (derived during variography processing above) was scaled to have a total sill of 1 and a low nugget near 0 (0.02). This scaling was corroborated in Geostatistical Analyst using the inputs below as model parameters (Figure 16).

Normal Score Variogram Modeling of Entire Soil Moisture Dataset:

Nugget 0.02

<u>Model No. 1-</u>
Type- Exponential
Partial sill- 0.17
Major range- 50
Minor range- 50

<u>Model No. 2-</u>
Type- Spherical
Partial sill- 0.81
Direction- 64
Major range- 771
Minor range- 428

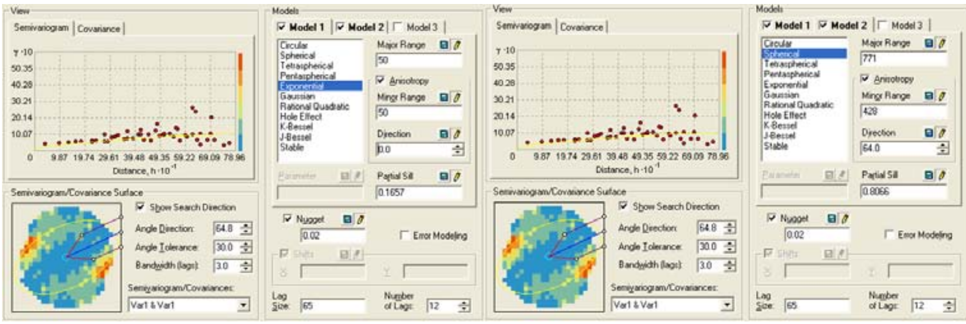


Figure 16. Semivariogram of normal-scored soil moisture data. Left is the first nested transitive structure (Model 1) and right is the second nested transitive structure (Model 2). Notice how the parameter values match those used in SGSIM.

It is typically desirable to know how many SGSIM realizations were required to reach a maximum difference, between realizations, of 5% of the soil moisture mean (Deutsch and Journel 1992). The soil moisture mean was ~4.5 and 5% of the mean was ~0.225%. Ten realizations were initially performed and the differences between the simulated maps were analyzed. The maximum difference (+/-) between the first and the tenth realization was 3.05 (note: a difference of <= 0.225 (<= 5 % of simulated mean soil moisture) was the target difference). Realizations were continued and the maximum magnitude of difference continued to decrease (Figure 17). A plot was constructed of these differences against the number of realizations to estimate the number of realizations needed (Figure 18). Based upon these data approximately 200-250 realizations were needed.

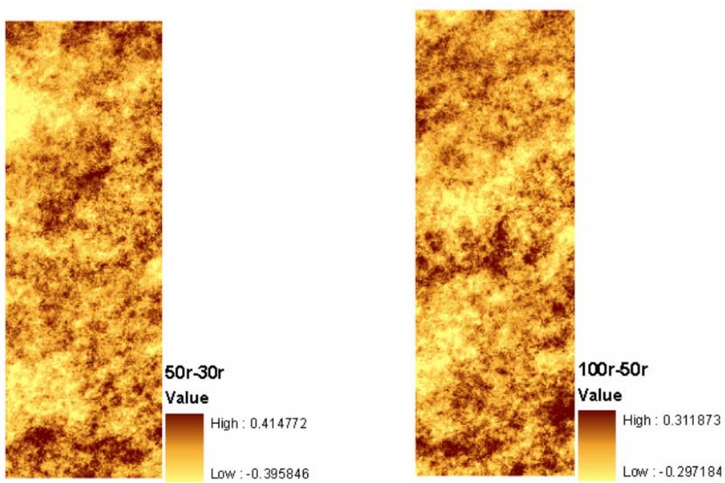


Figure 17. Comparison maps showing the magnitude of difference between 50 and 30 realizations (left) and between 100 and 50 realizations (right). Notice how the magnitude of difference is decreasing with increasing simulation realizations.

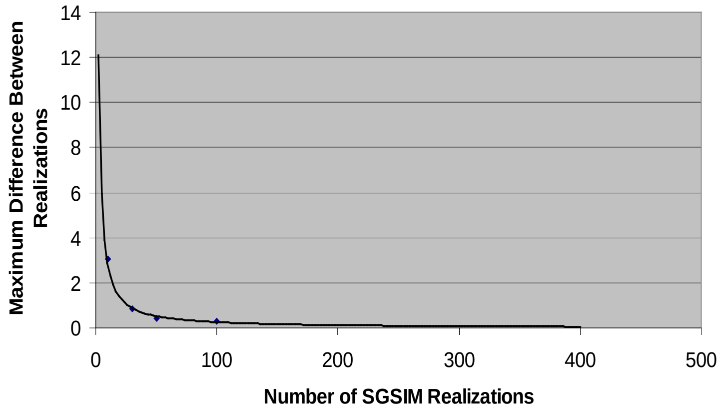


Figure 18. Plot of realizations to the difference between realizations. There are 4 plotted points on the graph at 10, 30, 50, and 100 realizations. From this plot it was determined that 200-250 realizations were needed to return a difference of 0.225 or less.

A total of 250 sequential Gaussian simulation realizations were performed which resulted in a difference of < 4 % of the soil moisture mean (i.e., within the target difference of +/- 5.0 %).

SOIL MOISTURE MODEL COMPARISONS AND CONCLUSIONS

The individual prediction models, created through ordinary kriging, for each grazing treatment were compared to the sequential Gaussian simulated prediction model (Table 6). SGSIM always resulted in a lower magnitude of difference when compared to the ordinary kriging model. This may be due to the autocorrelation structure of each individual treatment which was more difficult to infer than for the entire dataset (in which SGSIM parameters were based upon). The degree of uncertainty in modeling the autocorrelation structure likely propagated through the prediction comparisons.

Table 6. Comparison of SGSIM and the prediction model with the entire dataset (ordinary kriging) compared to each individually predicted map. The magnitude of difference that occurs with SGSIM is always smaller. Differences are expressed in volumetric water content (VWC) by percentage (%).

	SGSIM (250 Realizations)	**Entire Dataset**	**SHPG Treatment**	**Total Rest Treatment**	**Rest-Rotation Treatment**
SGSIM (250 Realizations)	N/A	2.16074	1.755661	1.355103	2.17733
Ordinary Kriging	2.16074	N/A	2.86102	2.0484	2.82802

Analysis of the difference between the SGSIM soil moisture model (with 250 realizations) and the ordinary kriging prediction model was conducted. The comparison is shown in Figure 19.

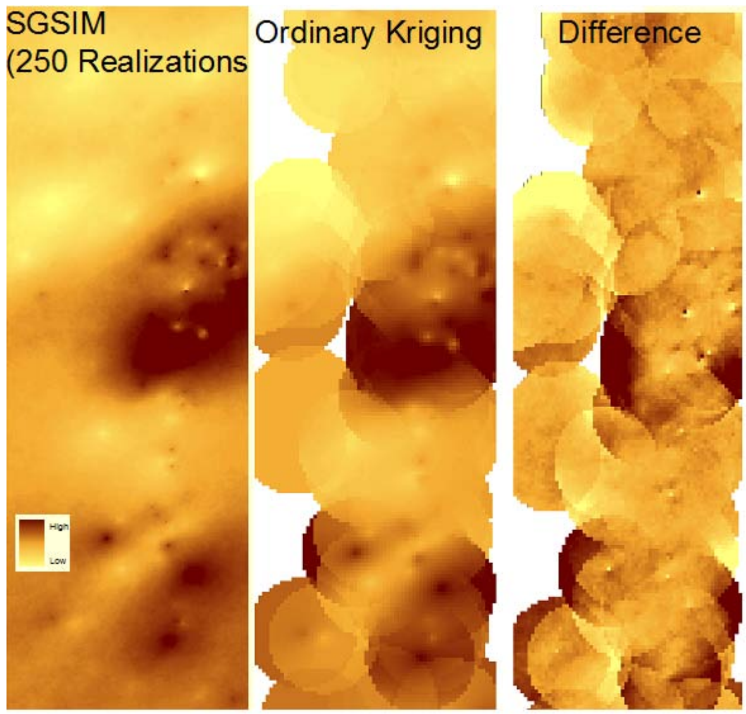


Figure 19. Comparison of the SGSIM model with 250 realizations (left) to the ordinary kriging prediction model (center). The difference model shows a maximum difference of 2.16. Higher difference frequently falls in areas located near the borders (fences) between grazing treatments or areas of less dense sampling.

The maximum difference between these models was 2.16. In all comparisons, the highest differences appear at the edges of data poor areas. Also, there were often high value differences near the borders of each grazing treatment. This degree of uncertainty was not necessarily acceptable, but understandable given the actual physical characteristics of fences and, as was previously shown, the mean soil moisture differences between treatments were significant. The highest squared differences of the semivariogram cloud were usually located near these same boundaries. In conclusion, the highest areas of uncertainty are in data poor areas and in geographic areas near or at grazing treatment transitions. For future sampling, it would be beneficial to measure more soil moisture values in these areas of concern. Overall, it is concluded that sequential Gaussian simulation with 250 realizations proved the most reliable in estimating the local soil moisture mean.

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Effect of Grazing Treatment on Soil Moisture in Semiarid Rangelands

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ABSTRACT

The rangelands of southeastern Idaho are important from both an ecological and economic perspective. Consequently, assessing and monitoring rangeland health is also important. Soil moisture is a key rangeland health parameter as it is the principal limiting factor in semi-arid ecosystems. While numerous factors may affect soil moisture, this paper focuses upon the effect of grazing on soil moisture using three treatments within the same soil association. The treatments, simulated holistic planned grazing (SHPG), rest rotation (RESTROT), and total rest (TREST) were treated with 36, 6, and 0 animal days per hectare respectively. Soil moisture was measured with 36 pseudo-randomly placed Decagon ECH_2O (EC-10) capacitance sensors during the years 2006, 2007 and 2008. Statistical analyses revealed differences in percent volumetric water content (%VWC) among all treatments in each year save for the comparison between the RESTROT and TREST pastures. In all cases, the SHPG pasture had the highest %VWC and within pasture comparisons indicated very little difference across each individual pasture. Mixed procedure models in SAS indicate strong environmental and treatment effects as explanatory variables for the observed difference in %VWC. Results of vegetation transect analysis indicated no difference in percent shrub cover for the two production treatments (SHPG and RESTROT), but a difference in the amount of litter present in later years of this study. It was concluded that management decisions (grazing and rest) can have substantial influence upon soil moisture and that even within production systems, soil moisture can vary substantially as a result of animal impact and the duration of grazing within a growing season.

KEYWORDS: grazing, volumetric water content, VWC, EC-10, capacitance sensors

INTRODUCTION

Southeastern Idaho is a region where the high-desert plains of the Snake River exist alongside mountain ranges. The economy of this semi-arid region is varied, but geographically dominated by farming and ranching industries. Ecologically, the sagebrush-steppe rangelands of southeastern Idaho provide important habitat for Greater sage-grouse (*Centrocercus urophasianus*) and other sagebrush-obligate species (Fischer et al. 1993). Urbanization, ranching, farming, fire prevention efforts, and invasions of non-indigenous plant species have impacted the vegetation in this area (Whisenant 1990) and for these reasons the rangelands of southeastern Idaho are particularly appealing for researchers examining the effects of drought, global climate change, and desertification on rangeland ecosystems and rangeland health.

The term rangeland health describes an important concept, but is fraught with varying definitions and connotations (National Research Council 1994, Savory 1999, Williams and Kepner 2002, O'Brien et al. 2003, Pellant et al. 2005). However, one commonality exists amongst these definitions, the importance of ground cover for proper hydrologic function (O'Brien et al. 2003). While hydrologic function has been defined as the ability of rangelands to capture, store, and release water (Pellant et al. 2000), it is difficult to accurately measure and monitor the inputs and outputs in the field. Instead, several indicators have been developed to characterize hydrologic function with percent bare ground exposure and soil moisture being some of the most commonly applied and accepted indicators (Booth and Tueller 2003, Taylor 1986). Indeed, Thomas and Squires (1991) argue that soil moisture is the principal determinant of productivity and the primary driver of rangeland condition in semi-arid ecosystems.

Soil moisture is an important environmental indicator of both the soil-water balance and of a soil's ability to regulate the hydrologic cycle. Soil water content (expressed as either percent water by weight, percent water by volume, or cm of water per cm of soil) can range from 0.05 g/g (5.0%) in xeric regions to 0.50 g/g (50%) or above (Werner 2002, GLOBE 2005) in more mesic areas. Various methodologies exist to measure soil moisture (electrical resistance blocks, tensiometers, gravimetric calculations, neutron probe, time domain reflectrometry, and capacitance probes) with some being more accurate and acceptable than others (Werner 2002). Regardless of the methodology used to estimate soil moisture, site specific calibration curves must be developed (GLOBE 2005).

The depth at which soil moisture instruments are placed is important if results are to be meaningful. For most rangeland applications, instruments should be located within the root zone of the site-specific plant community. It has been established that soil water content is dependent upon soil type, structure, porosity, and organic matter (Werner 2002). In addition, soil water content can be affected by changes in vegetation, runoff from adjacent roads, as well as other factors. The goal of this study was to determine if soil water content is also affected by land management decisions (e.g., grazing and rest) within semi-arid sagebrush steppe rangelands.

METHODS

Study area

Soil moisture data were collected at the O'Neal Ecological Reserve, an area of sagebrush-steppe rangelands in southeastern Idaho approximately 30 km southeast of Pocatello, Idaho (42° 42' 25"N 112°

13' 0" W), where many local-scale rangeland studies are being conducted (Figure 1). The O'Neal Ecological Reserve (http://www.isu.edu/departments/CERE/o'neil.htm) was donated to the Department of Biological Sciences at Idaho State University by Robin O'Neal. The O'Neal Ecological Reserve receives < 0.38 m of precipitation annually (primarily in the winter) and is relatively flat with an elevation of approximately 1400 m. The dominant plant species include big sagebrush (*Artemisia tridentata*) with various native and non-native grasses and forbs, including Indian ricegrass (*Oryzopsis hymenoides*) and needle-and-thread (*Stipa comata*). Soils in the O'Neal study area are homogeneous and of the McCarey series-McCarey variant soil association. These shallow, well-drained soils lie over basalt flows and were originally formed from weathered basalt, loess, and silty alluvium (USDA NRCS 1987).

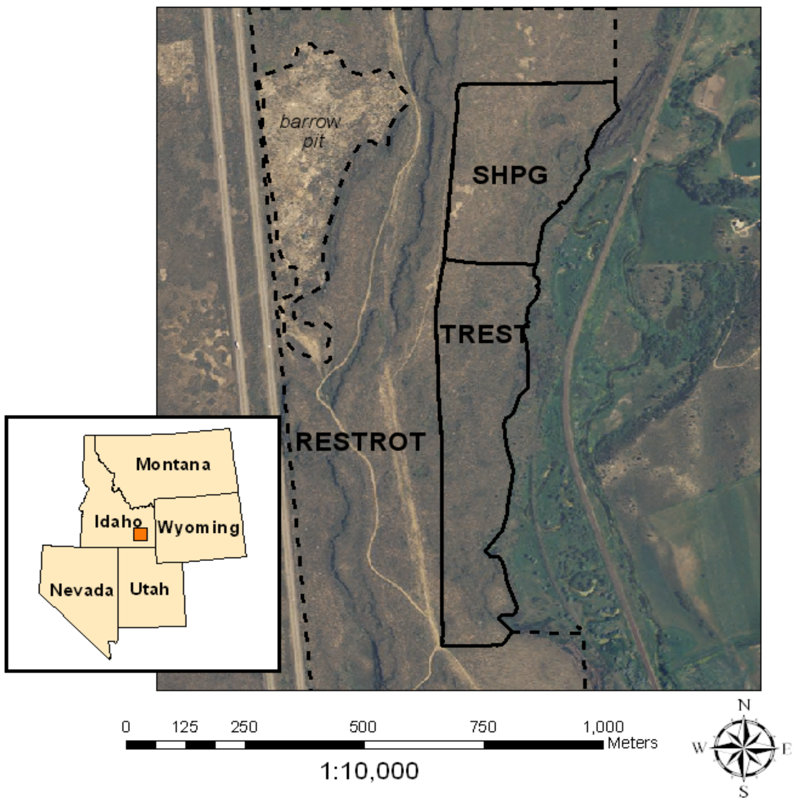

Figure 1. The O'Neal study area. The rest rotation pasture extends beyond this map to both the north and south. Note: no samples were taken from the barrow pit in the northwest corner of this map for any part of this study.

Field data

In 2005 and prior to any experimentation, the study area was sampled (n = 60) to establish pre-treatment vegetation cover conditions. In addition, hi-resolution (0.15 m) aerial imagery was acquired to provide a census of ground cover conditions that could be revisited in the future after fences were constructed and grazing treatments were implemented. Ocular estimates of percent cover were made for bare ground, litter, grass, shrub, and dominant weed. Cover was classified into one of nine classes {1) None, 2) 1-5%, 3) 6-15%, 4) 16-25%, 5) 26-35%, 6) 36-50%, 7) 51-75%, 8) 76-95%, and 9) > 95%} and all observations were made by viewing the vegetation perpendicular to the ground.

Treatment pastures were fenced in late summer 2005. In 2006, 2007, and 2008, the study area was sampled to monitor each treatment pasture. For each sample plot (n = 50 sample plots/pasture) two-10 m line transects were arranged perpendicular to each other and crossing at the 5 m mark of each line transect. Using the point-intercept method, observations were recorded every 0.2 m along each 10 m line, beginning at 0.10 m and ending at 9.8 m (n = 50 observations per line or 100 observations per plot). Percent shrub, grass, and litter cover were estimated in this fashion as was bare ground exposure. Beginning in 2007, forage biomass was measured using a plastic coated cable hoop 2.36 m in circumference (0.44 m^2). The hoop was randomly tossed into each of four quadrants (NW, NE, SE, and SW) centered over the sample point. All vegetation within the hoop that was considered forage for cattle, sheep, and wild ungulates was clipped and weighed (+/- 1g) using a Pesola scale tared to the weight of an ordinary paper bag. Grasses and forbs were weighed separately while woody species (i.e., sagebrush) were not clipped or included in the forage biomass measurements. The measurements were later used to arrive at an estimate of forage expressed in pounds per acre and kilograms per hectare (Sheley et al. 2003).

Instrumentation

Thirty-six Decagon ECH_2O (EC-10) capacitance sensors were installed across the O'Neal study area (Figure 2) in spring 2006 with 12 probes used in each of three treatment pastures (SHPG, RESTROT, and TREST). The EC-10 capacitance sensors (+/- 2% accuracy) used for this study were buried at a depth of 10cm. This depth was selected as it is within the root zone of the sagebrush-steppe plant community and at a depth where soil moisture responds rapidly to precipitation events and plant water use. More shallow placements were avoided as the sensors were more likely to be moved or damaged by livestock, rodents, and freeze/thaw cycles. Deeper placements were not possible in all sites across the study area due to underlying rock. The sensors were placed pseudo-randomly as true random placement was not possible because of numerous rock outcroppings and the concern that cattle would disturb or destroy the probes and data loggers if placed along existing trails or near water tanks. Nine data loggers were used (three per pasture) with four EC-10 capacitance sensors attached to each data logger. The EC-10 capacitance sensors were placed the maximum distance away from the data loggers as allowed by the data cables (approximately 18m).

In June 2006, six soil core samples (15.31 cm^3) were removed from the ground immediately adjacent to six EC-10 probes (approximately 15% of the probes were sampled, two from each treatment pasture). The soil was weighed (+/- 1 g) and stored in marked plastic bags for further analysis. The samples were then oven-dried and weighed again. Using these data, soil bulk density (g/cm^3), water volume (ml), and volumetric water content (VWC m^3 water/ m^3 soil) were determined. VWC (Y-axis) was regressed against raw probe output values (X-axis) to arrive at a line-of-best-fit and quadratic calibration function using third-order polynomial regression. The calibration equation (R^2 = 99.7) used for this study was:

$$Y = 4.86E\text{-}07x^2 + 6.22E\text{-}05x - 7.81E\text{-}02 \qquad \text{(Eq. 1)}$$

where Y = calibrated volumetric water content (m^3 / m^3)
x = raw output values from the EC-10 capacitance sensor

Percent volumetric water content was found by multiplying the calibrated VWC by 100. All soil moisture values given in this paper will be expressed as %VWC.

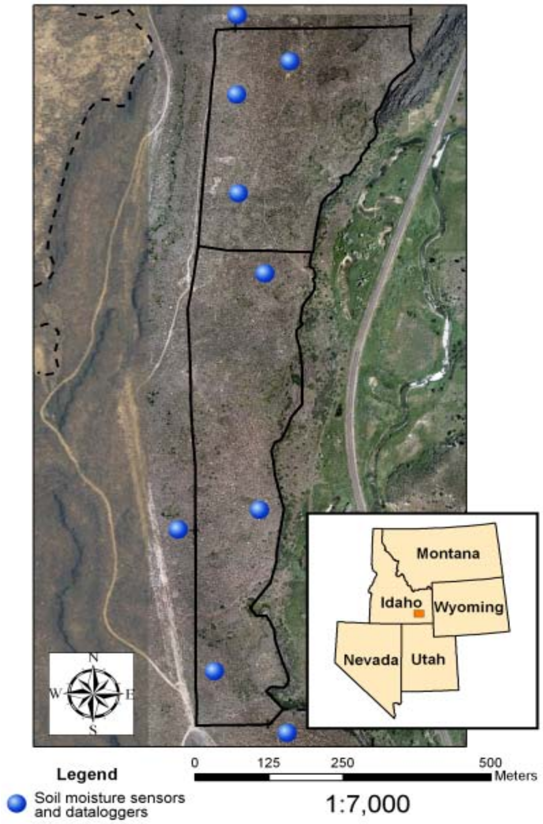

Figure 2. The location of the soil moisture sensors followed a star-like pattern around the dataloggers (shown as large dots on the map). Placement was pseudo-random and avoided both rock outcrops and existing cattle trails.

Soil moisture measurements were collected every six hours beginning 8 July 2006 and throughout the duration of this study (1 September 2008). All data were calibrated (using the equation above) and stored in an ArcSDE Geodatabase along with all spatial, temporal, and raw probe data. For the purposes of this study, soil moisture data were analyzed for the growing season only (i.e., through August 31st).

Also present at the O'Neal Ecological Reserve was a Davis Vantage Pro2 Weather Station (http://www.davisnet.com). Since June 2006, the O'Neal weather station has measured and recorded temperature, humidity, barometric pressure, wind speed and direction, precipitation, solar radiation, and solar energy every two hours. In addition, the Vantage Pro2 weather sensor also calculates dew point, various heat indices, and evapotranspiration (ET_0). Evapotranspiration is calculated and recorded as hourly potential ET_0 (in mm) using measured and calculated variables (Jensen et al. 1990, Davis 2006). Due to the small size of the O'Neal Ecological Reserve uniformity of environmental conditions which may affect soil moisture was assumed.

Grazing

Prior to this experiment and the construction of additional fencing, the entire study area (1491 ha) was managed as a single unit under a rest-rotation grazing system. For over two decades cattle grazed at low density (approximately 300 head) for long periods of time (30 days). Late in 2005, the study area was divided into three treatment pastures. The first was a simulated holistic planned grazing (SHPG) pasture where cattle graze at high density (66 AU/ 11 ha) for a short period of time (6 days) during the first week of June each year (2006-2008). The second treatment was a rest-rotation (RESTROT) pasture where cattle graze at low density (300 AU/ 1467 ha) for long periods of time (30 days) during the month of May each year. By following this grazing schedule, both production pastures were grazed at as near the same time as was logistically possible. The third treatment was a total rest (TREST) pasture (13 ha) where no livestock grazing has occurred since June 2005.

Statistical analysis

Pre-treatment shrub, grass, and litter cover, and bare ground exposure were compared between pastures using ANOVA (i.e., SHPG was compared with RESTROT, SHPG was compared with TREST, and RESTROT was compared with TREST) to determine if a difference pre-existed, which could account for any observed differences in %VWC of the soils.

An inverse relationship was expected between soil moisture and percent cover when all other factors were constant (precipitation, soil association, etc) across the study area. This relationship suggests that the treatment pasture having the highest soil moisture should have the lowest percent cover of vegetation. To investigate this, ANOVA was used to compare shrub cover (primarily Wyoming big sagebrush [*Artemisia tridentata* Nutt. ssp. *wyomingensis* Beetle & Young]) between pastures using field data collected in 2007 and 2008. In addition, since litter acts as mulch and can affect the % VWC of soils, differences in percent litter within each treatment pasture were investigated using point-intercept transect data from 2007 and 2008. ANOVA was used for pair-wise comparison of treatments (i.e., SHPG and RESTROT, SHPG and TREST, RESTROT and TREST).

Differences in forage biomass were investigated to help understand any observed differences in %VWC of the soils. To accomplish this, forage biomass estimates (kg/ha) were compared between treatment pastures using ANOVA.

Daily average %VWC was calculated for each treatment pasture (n = 48 [12 probes were located in each pasture with four measurement made per day]). In addition, weekly average %VWC was calculated for each treatment replicate (three data loggers were located in each pasture and treated as replicates). Four spreadsheets were prepared, one for 2006 (8 July 2006 through 31 August 2006), another for 2007 (1 April 2007 through 31 August 2007), a third for 2008 (1 April 2008 through 31 August 2008), and a fourth for 2006-2008 together with data arranged in week, year, data logger, and mean %VWC columns). The former yearly spreadsheets contained mean %VWC arranged in columns representing the three treatment pastures (SHPG, RESTROT, and TREST). ANOVA were calculated comparing pairs of treatments individually (i.e., SHPG and RESTROT, SHPG and TREST, RESTROT and TREST) within each year. To better account for the interactive effects of treatment and the environment (weekly and annual differences in soil moisture due primarily to precipitation, and temperature) and to provide a more robust and conservative test, a mixed procedures model was applied using SAS software and 2007 and 2008 data (note: the data from 2006 was not used in this test as the same number of weeks were not sampled causing a lack of convergence error in the SAS procedure). The fixed effects calculations followed Prasad-Rao-Jeske-Kackar-Harville methodologies while the degrees of freedom calculation followed the Kenward-Roger method.

Spatial heterogeneity of the soil was investigated to determine the degree of variability that existed within the soils. To accomplish this, 2006 soil moisture data were used (these data would tend to show the least treatment effect) and each pasture was sub-sampled by selecting six EC-10 capacitance sensors (two diagonally juxtaposed sensors were selected from each data logger [with four sensors each]) and the daily mean %VWC was compared with the daily mean %VWC for the remaining six EC-10 capacitance sensors in the same treatment pasture. ANOVA was used to compare within pasture daily mean %VWC.

RESULTS AND DISCUSSION

Results of analyses comparing pre-treatment conditions within each pasture indicate no difference in ground cover pre-existed with the exception of shrub cover, which was found to be slightly higher in the TREST pasture than in the SHPG pasture (Table 1). No other differences were found in other cover classes or treatment pastures.

Table 1. Comparisons of pre-treatment (2005) land cover conditions and results of statistical analyses

			Median Cover Class	
Treatment	**Shrub**	**Grass**	**Litter**	**Bare Ground**
SHPG	1-5%[1]	1-5%	16-25%	36-50%
RESTROT	1-5%	1-5%	16-25%	36-50%
TREST	16-25%[1]	1-5%	6-15%	26-35%

[1] indicates a statistical difference was found between these two areas (P < 0.001)

The results of vegetation cover analyses during the experiment indicate no difference in percent cover of shrubs between the SHPG and RESTROT pastures (P = 0.687 and P = 0.584) in both 2007 and 2008 respectively, while a difference was found between the SHPG and TREST pasture (P = 0.002) in 2007. This difference was not seen in the 2008 sampling however (P = 0.417) and given the heterogeneity of semi-arid rangelands and the fact that specific sample points were not revisited each year it is noteworthy that the between pastures comparison (where within year environmental conditions were constant) revealed no difference in percent cover of shrubs in most cases.

The ANOVA tests comparing percent litter revealed statistically significant differences among all three treatments (P < 0.001) beginning in 2007 but no difference prior to this time. Pair-wise comparison showed significant differences between the SHPG and RESTROT pastures (P < 0.001) in both 2007 and 2008, as well as between the SHPG and TREST pastures in 2007. No difference in litter was found between the SHPG and TREST pastures in 2008 (P = 0.07) and no statistical difference was found between the TREST and RESTROT pastures (P > 0.001) at any time throughout this study.

These results suggest that total rest and rest-rotation (partial rest) treatments have similar effects on litter and that treatment has the ability to modify litter cover. Litter affects soil nutrients and soil structure as its decay adds nutrients to the soil, improves soil structure, and reduces soil erosion (Nagler et al. 2000). Soil temperature, a controlling factor for soil moisture as it affects evaporation, is also affected by the amount of litter (Davidson et al. 1998). Consequently, the changes observed in the SHPG treatment pasture appear to be the result of several interactive affects (high intensity short duration grazing, animal impact, and increased litter cover) producing a positive feedback cycle which may ultimately improve the condition and sustainability of rangelands (Redman 1978, Snyman 2002, Fynn 2008). Naeth et al. (1991a) reported that litter itself can hold water and thus affect the soil moisture. The authors imply that water holding capacity (WHC) depends on vegetation type which is influenced by grazing. Naeth et al. (1991b) have also studied grazing impacts on litter and soil organic matter with reference to grazing regimes of light to heavy intensities grazed early, late, and continuous throughout the growing season. They found more medium- and small-particle sized organic matter occurred in grazed treatments compared to un-grazed (i.e., total rest) pastures. Recently Neufeld (2008) evaluated how litter affects soil moisture. Through that study it was concluded that the relationship between litter and soil moisture is a complex one, dependent upon climate, landscape, soil properties and vegetation type.

Forage biomass comparisons indicate more above-ground grass biomass was found in the SHPG pasture ($\underline{x}$ = 58.6 kg/ha [S.E. = 3.2]) relative to that found in the RESTROT pasture ($\underline{x}$ = 39.5 kg/ha [S.E. = 3.8]) in 2007 ($P < 0.001$). This difference was not seen in 2008 ($P = 0.17$) although the mean above ground grass biomass was slightly higher in the SHPG pasture ($\underline{x}$ = 79.9 kg/ha [S.E. = 5.1]) than in the RESTROT pasture ($\underline{x}$ = 68.5 kg/ha [S.E. = 6.4]). The difference observed is most likely attributable to how livestock utilized the pastures, the time span between when the cattle were removed from the pastures and when the pastures were sampled, and differences in precipitation. From January 1st to June 30th 0.105 m of precipitation fell in 2007 whereas 0.097 m of precipitation fell over the same time period in 2008. Significant differences ($P < 0.001$) were also observed between the production pastures (SHPG and RESTROT) and the TREST pasture ($\underline{x}$ = 131.9 kg/ha [S.E. = 10.2] and $\underline{x}$ = 239.2 kg/ha [S.E. = 24.0] in 2007 and 2008, respectively) in both 2007 and 2008. This result may be somewhat misleading however as all pastures were sampled following grazing. Consequently the TREST pasture was expected to have higher above-ground grass biomass.

Analyses comparing daily %VWC among treatment pastures indicate significant difference (P < 0.001) when all treatments are compared at once. Pair-wise comparisons indicate statistically significant differences between the SHPG and RESTROT pastures in 2006, 2007, and 2008 (P < 0.001) and between the SHPG and TREST pastures in 2006, 2007, and 2008 ($P < 0.001$). No difference in %VWC was found between the RESTROT and TREST pastures in either 2006 ($P = 0.161$) or 2007 ($P = 0.749$) although differences were found in 2008 ($P < 0.001$) (Table 2).

Table 2. Mean %VWC comparisons by treatment

	$\bar{x}$ %VWC		
Treatment	**2006**	**2007**	**2008**
SHPG	23.3	44.1	45.8
RESTROT	19.7	34.8	34.7
TREST	19.2	31.9	29.8

Within pasture comparisons indicate very little difference existed in %VWC across each individual pasture. The SHPG pasture revealed the greatest heterogeneity ($P < 0.025$) while both the RESTROT and TREST pastures showed no detectable difference ($P = 0.15$ and $P = 0.12$ respectively). It is difficult to know if the difference observed within the SHPG pasture is due to an *a priori* difference in soils or an early observable effect of treatment. While it is impossible to know, it is most likely a combined effect of both treatment and soil heterogeneity.

Results from the mixed procedures model and type three test of fixed effects indicate the observed differences in %VWC at the O'Neal study area were principally due to weekly effects ($F = 91.87$ $P < 0.0001$) (e.g., early season %VWC differs from late season %VWC suggesting a purely environmental influence) followed by the year x pasture interaction ($F = 20.03$ $P < 0.0001$). This secondary effect indicates that while %VWC differs annually, it is differentially variable by pasture, suggesting both an environmental and treatment influence. The third significant explanatory effect was the week x year interaction ($F = 6.29$ $P < 0.0001$) while the final significant effect was attributable to the pasture variable alone ($F = 4.89$ $P = 0.05$). This latter effect indicates that the treatment applied within each pasture accounts for some significant portion of the total variability seen in %VWC at this study area and coupled with the year x pasture interaction, suggests that treatment has the ability to make substantial changes to rangeland soils.

The response of %VWC (Daily % VWC) to precipitation events was investigated using data collected in 2007 to better understand the hydrologic cycling dynamics within the study area and within each pasture (Figure 3). As expected, soil moisture content at 10 cm increased rapidly after precipitation events and declined at equivalent rates. During the summer months, the rate of soil water decline was much greater than autumn rates. Furthermore, while absolute %VWC is highest in the SHPG pasture (Table 2) the trend followed in all pastures is nearly identical.

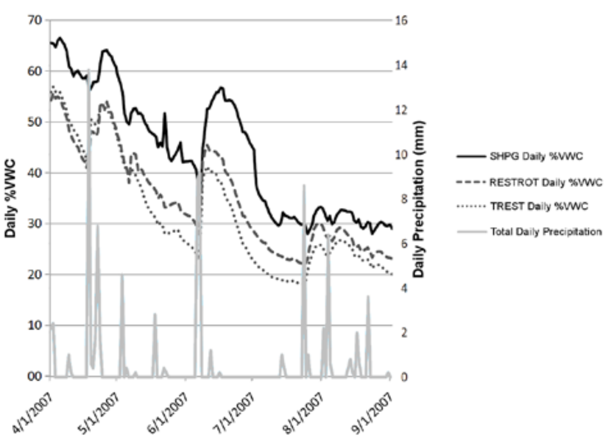

Figure 3. Soil moisture response in each treatment pasture relative to rainfall events during the summer of 2007 illustrates a rapid increase in response to precipitation followed by a decline at nearly equivalent rates.

Assessment of error and bias

The accuracy of the Decagon ECH_2O (EC-10) capacitance sensors was +/- 2%. Conservatively applying known instrumentation error indicates that if mean %VWC was within 4% for any two treatment pastures then the real difference between those treatments may be questionable even if they were found to be statistically different. This condition occurred only in 2006 (Table 2). All other comparisons do not satisfy the error condition tolerance of +/- 4% and are considered valid.

A potential bias of this study is related to the pseudo-random positioning of the Decagon ECH$_2$O (EC-10) capacitance sensors. Ideally, the sensors would have been placed in an absolutely random fashion, however this was not possible for two reasons: 1) the McCarey series-McCarey variant soil association found throughout the study area is typified by having very shallow bedrock (approximately 0.25 m) which precludes a true random placement of sampling probes and requires *in situ* placement adjustments, 2) the study area is actively grazed by cattle and placement of sampling probes could not be located close to trails or water sources as the increased presence of cattle would increase the probability of the probes, their buried wire connections and above ground data loggers would be damaged or destroyed. To minimize potential damage and avoid rock outcroppings we chose to use a pseudo-random location strategy where true random locations were first generated using Hawth's tools (within ESRI's ArcGIS) and final placement was decided during installation based upon field conditions and the considerations noted above. In all cases, final placement of the sensors was made as close to the randomly generated location as possible.

Another potential bias in this study and one the authors have tried to accommodate for is the uneven sampling duration. The Decagon ECH$_2$O (EC-10) capacitance sensors became operational on 8 July 2006 and continued in operation throughout this study. As a result, the 2006 growing season records do not include measurements made prior to July 8. This shortcoming was corrected in 2007 and 2008 as records from April 1 through August 31 were available and used in this study. For this reason, empirical comparisons of %VWC between 2006 and latter years were limited.

A potential error in this study relates to the frequency of daily soil moisture observations (4/day) and averaging. It is likely that soil moisture varies diurnally but if soil moisture levels varied disproportionately across the three treatment pastures an error could have been introduced. Such phenomena are unlikely however, as the soil association is homogeneous across all three treatment pastures. Daily soil moisture fluctuations were expected to be uniform and any slight error due to averaging was consistent across all treatments.

This study was part of a larger study focusing upon the use of remote sensing satellite imagery to detect changes in vegetation land cover. To augment understanding of detected changes, soil moisture sensors were deployed in 2006 concurrent with commencement of experimental grazing and satellite imagery acquisition. Soil type was the same (McCarey series-McCarey variant soil association [NRCS 1987]) across all experimental pastures and pre-treatment vegetation cover data (2005) showed little overall difference in shrub, grass, litter, or bare ground exposure, soil moisture was assumed to be similar prior to treatment. However, to draw a final conclusion regarding the effect of treatment on soil %VWC, pre-treatment conditions should be known, not assumed. While this study presents interesting trends and observations one cannot conclusively state that a given treatment tends to encourage higher soil moisture rates relative to another treatment. Observations made during this experiment are encouraging and illustrate that treatment is a statistically important effect. Furthermore the trend of continued divergence in %VWC among the treatments is interesting and appears promising (Figure 4). Future research should be directed toward answering this question using a larger replicated study with at least one year of pre-treatment data collection.

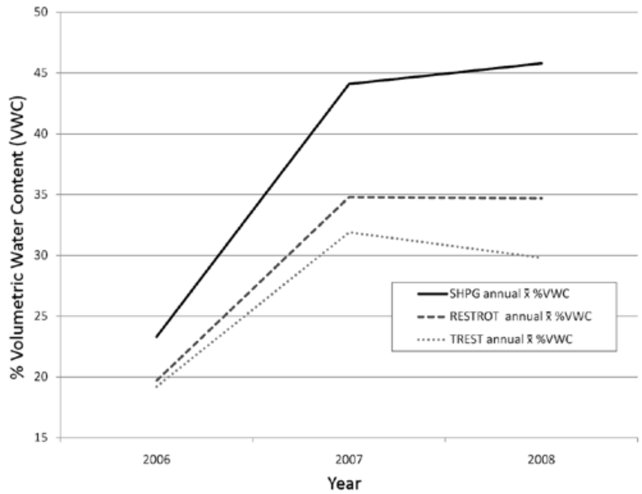

Figure 4. Mean annual %VWC within each treatment pasture. Note: 2006 data appear substantially lower than shown in subsequent years but this is believed to be a function of duration of sampling rather than real differences. In addition, note the continued increase in mean %VWC within the SHPG pasture and the decline in mean %VWC in the TREST pasture. These changes are most likely due to actual treatment differences.

Management Implications

Water absorption and retention capacity of soils depends upon soil type (e.g, sand, silt, and clay), porosity, and organic matter or colloidal content (Singer and Munns 1987, Werner 2002), vegetation cover, and numerous other factors. The effect of treatment on soil moisture is not well recognized although some studies have documented the effect of grazing on carbon dynamics (Haferkamp and Macneil 2004) or evaluated the effect of grazing on various physical properties of soil (Wheeler et al. 2002).

This study demonstrates that season-long mean soil moisture (expressed as %VWC) can vary significantly even within areas with the same vegetation cover and soil type (McCarey series-McCarey variant soil association) and presumably the same soil porosity and organic matter content. The latter may not be entirely true however and was not analyzed as part of this study. Indeed the difference in treatment may have altered the porosity and organic matter of the soils within each treatment pasture, thereby offering one explanation of how these soils were able to retain more water throughout the growing season (Naeth et al. 1991b). In addition, the increase in litter as a result of the treatment has the ability to increase the soil’s ability to retain water by both adding organic matter through decomposition and by acting as mulch which shades the soil from direct solar contact and also cools the soil which reduces loss of moisture through evaporation. These interactive effects may ultimately lead to changes in plant community composition if the differences in soil characteristics (moisture and temperature) create a microenvironment that favors certain plant species.

CONCLUSIONS

While soil type and shrub cover were effectively the same across the study area, mean % VWC was found to differ. Pair-wise comparisons indicate that mean % VWC for the SHPG treatment pasture was significantly higher than that found in the RESTROT or TREST treatment pastures while mixed procedures modeling in SAS revealed a strong environmental as well as treatment effect. Animal impact and the duration of grazing (i.e., spatio-temporal effects) may be responsible for some of these differences. Interrelated with animal impact, increased litter cover in the SHPG pasture may play a role in the observed soil moisture differences. Although the relationship between litter and soil moisture is complex, the current literature (Naeth et al. 1991a; Neufeld 2008) suggests that litter can affect soil moisture and soil organic matter. Holistic planned grazing appears to offer a management alternative with beneficial results measured on this landscape. In light of these encouraging results, additional studies are warranted relative to the merits of holistic planned grazing and the ability of treatment to favorably modify landscapes.

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Forecasting Rangeland Condition in Southeastern Idaho using GIS

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ABSTRACT

In light of concerns regarding global climate change, biodiversity loss, and desertification, the monitoring and accurate forecasting of land cover change is an important and yet challenging endeavor. The climatic variability observed in semi-arid and arid ecosystems makes accurate predictive models increasingly challenging over even short time periods. This study used Idrisi Land Change Modeler to develop predictive rangeland condition models for 2008 (short-term) and 2012 (long-term) for semi-arid rangelands in southeast Idaho using imagery from 2003 and 2007. The short-term model was validated using imagery acquired in 2008 resulting in poor overall accuracy (0.49). The observed performance may not be indicative of the potential of Idrisi software, however it was concluded that accurately forecasting change in semi-arid ecosystems requires the use of multiple years of input data to correctly establish variance and trend. The predicted rangeland condition model for 2012 will be validated at a later time and its accuracy is expected to be dependent upon the similarity of 2012 precipitation relative to the precipitation patterns of 2003 and 2007.

KEYWORDS: Predictive modeling, cellular automata, artificial neural networks, precipitation variability

INTRODUCTION

Rangelands occupy a large portion of the earth's land surface (Huntsinger and Hopkinson 1996, Branson et al. 1981) and are home to many species of plants and animals uniquely adapted to semi-arid ecosystems (IUCN 2006). Semi-arid rangelands, while marginal and frequently undesirable for cultivation, are important areas of livestock production throughout the world. However, due to the very same characteristics that lends them to livestock production (e.g., unreliable and seasonal precipitation, rocky soils, and steep slopes); rangelands tend to be brittle environments (Savory 1999) with increasing concerns for biodiversity loss and desertification. Traditional scientific investigation – and perhaps human nature itself—seeks to solve complex problems by subdividing the problem into manageable pieces and the simple fact that numerous scientific disciplines exists bears out this observation (Funtowicz and Ravetz 2003). In range science, land degradation has typically been attributed to overgrazing with very little scientific inquiry investigating alternative hypothesis or testing this assumption relative to over-rest. Consequent to observed land degradation –regardless of its cause—a classification describing the degree of degradation was needed to facilitate comparison with future assessments used to describe a trend and/or the effect of remediation (Washington-Allen et al., 2006). To facilitate discussion and communication processes such as these required names and in this case, the terms rangeland condition (Bedell 1998) and later, rangeland health (National Research Council 1994) were coined. Regardless of the original intent, applied terms always take on varying "flavors" as they are learned by others and used by others in subsequent communications. In some cases, terms become buzz-words and ultimately lose much of their original intent.

Regardless of the term applied to the process, assessing the degree of land degradation is important. In this study, the term rangeland condition was used with no additional "baggage" intended. To help quantify landscape condition and avoid qualitative assessment, satellite imagery was used. Two condition states were produced, the first at an "early date" and the second at a "later date". Using these condition states and the change in condition over time, trend is established. Once a trend has been established the possibility to forecast condition into the future is possible assuming all treatment and environmental variables remain along the same trend vector. Herein lies the crux of such a simplistic approach, for it is unlikely that the environmental conditions which helped create the current condition will remain static in the future (precipitation, temperature, and the interaction of these two variables over time). Further, in the face of known degradation, it is equally unlikely that no change in land use or land tenure (Cummins 2009) will be effected as well.

For these reasons, forecasting change is an important and challenging endeavor (NCSE 2005) and numerous techniques have been developed. In general, predictive land use and land cover (LULC) models can be categorized as either 1) an equation-based, 2) statistical 3) matrix-based, 4) system, 5) expert, 6) evolutionary, 7) cellular automata, 8) agent-based, 9) multiple agent-based, or 10) a hybrid model (Parker et al. 2003).

Equation-based models apply mathematical equations or algorithms to arrive at an assumed stable state of equilibrium which is both derived and solved mathematically (Sklar and Costanza 1991; Chuvieco 1993). Statistical models differ from equation-based models in that they tend to rely upon various forms of regression analyses to predict LULC (Ludeke et al 1990). By comparison, matrix-based models use matrix algebra and focus upon transition potentials to arrive at a prediction of future LULC (Sonis et al.

2007) while system models portray change as a flow from one step to another with various linkages between the steps that allow for interaction or feedback (Sklar and Costanza 1991). Expert models differ from the computationally intensive methods above in that they apply expert knowledge, rules, and probability to achieve a predicted LULC. Whereas expert models frequently apply Bayesian or Dempster-Schaefer theory (Eastman 1999), evolutionary models rely upon artificial neural networks (Mann and Benwell 1996) to make similar predictions of LULC.

Cellular automata models operate over a grid of cells which change over time due to both transition potentials and/or interaction of the focal cell with adjacent cells. Transition potentials are frequently modeled using Markov chain, a stochastic process that determines the future state of a cell based upon the present state of the cell and independent of the past state(s) of the cell (Li and Reynolds 1997). Two criticisms of cellular automata models are 1) they do not model human decisions or human agents (Parker et al. 2003) explicitly and 2) they are unlikely to correctly predict future states as the transition potentials do not account for political or other anthropic forces (Soares-Filho et al. 2002).

Agent-based models focus upon human actions which impact LULC by following a set of rules or behaviors. In contrast to cellular automata, agent-based models may fail to accurately model LULC by overstating the impact due to anthropic forces. One solution to the problems and criticisms of both cellular automata and agent-based modeling is the use of multiple agent-based models which apply cellular automata to predict the biophysical characteristics of a landscape along with agent-based modeling to describe the human decision-making process. In this way, multiple agent-based models may be able to accurately predict future LULC.

The application of LULC change models to semi-arid rangelands is not new. Li and Reynolds (1997) used cellular automata to model rangelands while others have modeled LULC change on rangelands using state-and-transition models (a system-based model) (Westoby et al. 1989; Laycock 1991; Bestelmeyer et al. 2003). Regardless of the specific approach taken, modeling LULC change on semi-arid rangeland is particularly challenging due to the high variability of precipitation and its cascading affects throughout the rangeland ecosystem (IUCN 1989; Khazanov 1994; Niamir-Fuller and Turner 1999). The present study sought to investigate predictive LULC change models for semi-arid rangelands using state-of-the-art software by first creating a short-term prediction of change and then validating that prediction using field observations/ measurements and satellite imagery collected during the time period of prediction. This paper describes the predictive modeling process, validation process, and the implications for future research and range management.

MATERIALS AND METHODS

Study Area

The O'Neal Ecological Reserve is an area of sagebrush-steppe rangelands in southeastern Idaho approximately 30 km southeast of Pocatello, Idaho (42° 42' 25"N 112° 13' 0" W), where many local-scale rangeland studies are being conducted (Figure 1). The O'Neal Ecological Reserve (http://www.isu.edu/ departments/CERE/o'neil.htm) was donated to the Department of Biological Sciences at Idaho State University by Robin O'Neal. The O'Neal receives < 0.38 m of precipitation annually (primarily in the winter) and is relatively flat with an elevation of approximately 1400 m. The dominant plant species include big sagebrush (*Artemisia tridentata*) with various native and non-native grasses and forbs, including Indian ricegrass (*Oryzopsis hymenoides*) and needle-and-thread (*Stipa comata*). Soils in the O'Neal study area are homogeneous and of the McCarey series-McCarey variant soil association. These shallow, well-drained soils lie over basalt flows and were originally formed from weathered basalt, loess, and silty alluvium (USDA NRCS 1987).

Three treatment pastures exist at the O'Neal Ecological reserve. The first was a simulated holistic planned grazing (SHPG) pasture where cattle graze at high density (66 AU/ 11 ha) for a short period of time (6 days) during the first week of June each year (2006-2008). The second treatment was a rest-rotation (RESTROT) pasture where cattle graze at low density (300 AU/ 1467 ha) for long periods of time (30 days) during the month of May each year. By following this grazing schedule, both production pastures were grazed at as near the same time as was logistically possible. The third treatment was a total rest (TREST) pasture (13 ha) where no livestock grazing has occurred since June 2005.

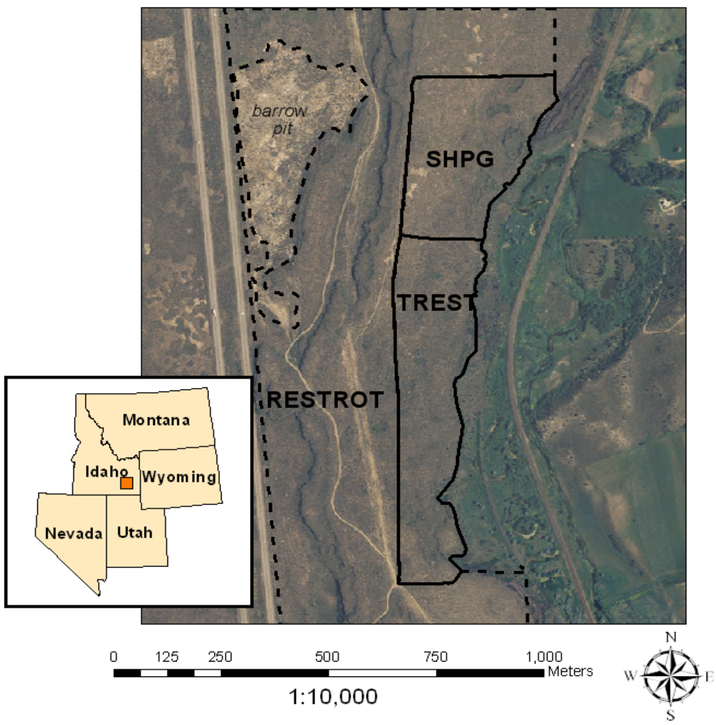

Figure 1. The O'Neal Study Area in southeast Idaho is comprised of three treatment pastures, simulated holistic planned grazing (SHPG), rest-rotation (RESTROT), and total rest pastures (TREST).

While many changes to the landscape are attributable to the environment (e.g., drought) (IUCN 1989) others may be attributable in varying degrees to anthropic forces, or rather, the effect of the human decision-making process (Khazanov 1994, Seligman. and Perevolotsky 1994, Niamir-Fuller and Turner 1999, Hill 2006). For instance, experiments already completed at the O'Neal study area have demonstrated the effect of both the environment (precipitation) and management treatment on soil moisture (Weber and Gokhale 2010). In this case, the SHPG pasture resulted in statistically higher soil moisture levels even when no difference existed in soil association or percent cover of shrubs, grasses, and bare ground. Indeed the only difference between these experimental pastures was the applied treatment and a resulting higher level of litter cover caused by the trampling activity of livestock. It was anticipated that the three treatment pastures will be forecast to diverge over time as a result of differences in land use.

Satellite Imagery

To forecast the future condition of a specific rangeland site it is beneficial to know both past and present conditions. To accomplish this, a minimum of two datasets are required: 1) an early land cover or land condition layer (D1) and 2) a later or present land cover/land condition layer (D2). With these data, trend *can* be established however the resulting perfect trend (two data points will be fit by a straight line resulting in an R^2 of 1.00) will be unable to account for the many perturbations between D1 and D2 as no other data are available. Ideally then, additional datasets will be available which describe land cover/condition between D1 and D2. For this specific study, satellite imagery was used to describe land cover/condition at the O'Neal study area.

An understanding of the phenology and vegetation community at the specific rangeland site being modeled (i.e., the O'Neal study area) is also beneficial. With this information, the analyst will be able to select datasets that are phenologically similar (Weber 2001) and thereby less complicated to compare to other datasets and establish a reliable trend. To illustrate, one can imagine being given a photograph taken in spring and comparing that photograph to another –of the same location—taken in late summer. The conclusions deduced from the study of such photographs would lead a person to believe that some dramatic changes have occurred (they have) and to erroneously establish a trend line that when forecast to future dates would lead to gross errors in prediction. To minimize this error, imagery was phenologically synchronized (cf. calendar-date synchronization) as well as logistically possible.

With the above considerations in mind, Landsat 5 TM and Satellite Pour l'Observation de la Terre 5 (SPOT 5) imagery were acquired between the years of 2003 and 2008 for the O'Neal study area (Table 1). All imagery was corrected for atmospheric effects using Idrisi Andes software and the Cos(t) methodology (Chavez 1996).

Table 1. Satellite imagery acquired to model land cover/condition, forecast, and validate future condtion.

Year	Date	Satellite platform
2003	August 24	Landsat 5 TM
2004	August 10	Landsat 5 TM
2005	August 13	Landsat 5 TM
2006	September 26	SPOT 5
2007	September 15	SPOT 5
2008	August 18	SPOT 5

Image Processing

Using atmospherically corrected imagery, normalized difference vegetation indices (NDVI) (Rouse et al. 1973; Tucker 1979) were calculated for each year. In addition, a moving standard deviation index (MSDI) was calculated for each year (Tanser 1997) using the red band from either Landsat 5 TM or SPOT 5 imagery.

All NDVI and MSDI layers were then tested for georectification error and co-registered (Weber 2006; Weber et al. 2008) to one another using 2004 National Agricultural Imagery Program (NAIP) 1 m aerial imagery as the reference layer. First order affine georectification was performed using ESRI ArcGIS software with nearest neighbor resampling. The resulting root mean square error (RMSE) did not exceed the size of ½ pixels (Weber 2006) and both georectification and co-registration was considered successful with minimal error propagating into subsequent analysis.

All Landsat-derived NDVI and MSDI layers (2003-2005) were resampled using nearest neighbor methodology to 10mpp spatial resolution to match the resolution of the SPOT-derived layers. While this process unnecessarily inflated the size of the Landsat layers it also allowed for us to retain all data in the SPOT layers used in 2006-2008. Lastly, all layers were windowed to the extent of the O'Neal study area to reduce processing time and confine forecasting results to the three treatment pastures that comprise the study area.

Rangeland Condition Classification

Annual NDVI and MSDI layers for the O'Neal study area were evaluated to determine a rangeland condition score following Tanser and Palmer (1999). In the present study, a matrix was applied to each NDVI and MSDI layer to re-classify each pixel relative to its land degradation status where NDVI values < 0.44 were considered degraded as were MSDI values > 0.032 (Tanser and Palmer 1999; Jafari et al. 2008). The annual rangeland condition score was determined by evaluating the above degradation status values and pixels were assigned: one (1) where both the NDVI and MSDI models indicated a degraded status, two (2) when the NDVI model indicated degradation but the MSDI model indicated non-degraded (good) condition, three (3) when the MSDI model indicated degradation but the NDVI model indicated good condition, or four (4) when both the NDVI and MSDI models indicated good condition. The resulting rangeland condition layer was used as the input land cover for subsequent forecasting models.

Land Cover Change Forecasting

Idrisi Andes software was selected to perform LULC forecasting using its land cover change modeler (LCM). The LCM process begins by calculating land cover change analysis using known/past change. To complete this process two image layers are required (i.e., early [2003] and later [2007] layers). The land cover change analysis routine calculates spatial trend which is used later in the forecast process. Next, transition potentials are determined and site and driver variables examined for their explanatory power. Once site and driver variables have been determined, a transitions sub-model is calculated. Using the derived models and input layers a predicted land cover layer is created using a multi-layer perceptron neural network.

The LCM was run twice in this study. First to produce a short-term forecast of change (2008) which was validated using data and imagery collected in 2008 and second to produce a long-term forecast of change (2012).

Validation

The short-term forecast of change was developed to predict land cover (i.e., rangeland condition score) in 2008. This forecast was validated using NDVI and MSDI layers acquired in 2008 and processed to determine actual rangeland condition score following the process described above. The actual rangeland condition layer was then compared to the forecast rangeland condition layer and an error matrix produced along with the Kappa index of agreement. In addition, a qualitative assessment of the forecasts was made by treatment pasture to better understand the predicted trend of change at the O'Neal study area.

RESULTS AND DISCUSSION

Validation of the 2008 forecast model reveals an overall accuracy of 49% (Table 2), producer accuracies ranging from 3% to 72%, and user's accuracies ranging from 20% to 58%. These results are poor and leave little hope for a successful forecast in 2012. Similar forecast results were observed within each treatment pasture (Table 3a-c) illustrating consistency of the LCM technique as well as its inaccuracy.

Table 2. 2008 predicted range condition score relative to actual range condition score for the O'Neal study area.

Range Condition Score	1	2	3	4	Sum of pixels	User's accuracy
1	7284	2664	73	81	10102	0.72
2	4009	8638	10	19	12676	0.68
3	4617	2807	222	589	8235	0.03
4	1468	710	124	173	2475	0.07
Sum of pixels	17378	14819	429	862	33488	
Producer accuracy	0.42	0.58	0.52	0.20	**Overall accuracy**	0.49

Table 3. 2008 predicted range condition score relative to actual range condition score for the SHPG treatment pasture (A), RESTROT treatment pasture (B), and TREST pasture (C).

A. Range Condition Score	1	2	3	Sum of pixels	User's accuracy
1	281	214	0	495	0.57
2	62	341	0	403	0.85
3	71	92	0	163	0.00
Sum of pixels	414	647	0	1061	
Producer accuracy	0.68	0.53	0.00	**Overall accuracy**	0.59

B. Range Condition Score	1	2	3	4	Sum of pixels	User's accuracy
1	1785	561	0	0	2346	0.76
2	695	4469	0	0	5164	0.87
3	900	402	0	0	1302	0.00
4	62	23	0	0	85	0.00
Sum of pixels	3442	5455	0	0	8897	
Producer accuracy	0.52	0.82	0.00	0.00	**Overall accuracy**	0.70

C. Range Condition Score	1	2	3	Sum of pixels	User's accuracy
1	124	107	0	231	0.54
2	48	514	0	562	0.91
3	145	380	0	525	0.00
Sum of pixels	317	1001	0	1318	
Producer accuracy	0.39	0.51	0.00	**Overall accuracy**	0.48

Closer examination of the existing and forecasted trends by treatment pasture allowed one to qualitatively assess predicted LULC at the O'Neal study area. This examination consisted of the calculation of a running average (cumulative $\underline{x}$ rangeland condition score was based upon a running average using scores from all previous years and the current year) and computation of resilience (equation 1). The resilience index describes how similar the rangeland condition score for a given year is compared to the cumulative $\underline{x}$ rangeland condition score.

$$Resilience = cumulative\ \underline{x}_{\ (rangeland\ condition\ score)} / current\ \underline{x}_{\ (rangeland\ condition\ score)} \qquad \text{(Eq. 1)}$$

Based upon observed rangeland condition scores for 2003, 2007, and 2008, and the 2012 forecast rangeland condition score, the SHPG pasture was determined to be most resilient ($\underline{x}$ resilience = 0.987 [S.E. = 0.016]) relative to both the RESTROT ($\underline{x}$ resilience = 0.950 [S.E. = 0.063]) and TREST treatment pastures ($\underline{x}$ resilience = 0.985 [S.E. = 0.065]).

The rangeland condition score for 2012 is forecast to increase for all three treatment pastures. The least improvement is predicted to occur in the SHPG pasture with the greatest improvement predicted to occur in the TREST pasture. Based upon past performance however, it is doubtful if the forecast will be correct. The O'Neal study area will continue to be monitored through the 2012 growing season and comparable satellite imagery will be acquired at that time. The imagery will be processed following the methods used in this paper and the observed rangeland score compared to the forecast rangeland score. Only at that time will one know the accuracy of the forecast model and methodologies described in this paper.

Assessment of Error and Bias

Idrisi's Land Change Modeler (LCM) software does not appear to produce accurate forecast models within semi-arid rangeland ecosystems. However, the Idrisi Andes release of LCM was fairly new and future versions of the software may produce more reliable models.

LCM appears to place much of its final prediction upon the initial trend of change which is determined by only two data points which are derived from an early image and a later image. The trend line established between any two points will always describe a perfect relationship (R^2 = 1.0) and can lead to gross errors within highly variable landscapes.

Semi-arid rangelands represent highly variable landscapes where changes are driven not just by intrinsic factors (e.g., topography and soil type), treatment, and land use decisions, but by environmental factors such as precipitation as well (Khazanov 1994; Niamir-Fuller and Turner 1999). As an example, the affect of increased precipitation on forage biomass can be substantial as evidenced in the semi-arid rangelands of southeast Idaho, where forage biomass measurements averaged 191.3 kg/ha in 2003, 289.7 kg/ha in 2004, and 488.1 kg/ha in 2005 (Sander and Weber 2006; Gregory et al 2008). When one then examines precipitation curves for the O'Neal study area between 2002 through 2007 (Figure 2) large differences are also seen in inter-annual accumulated precipitation. These differences are roughly correlated with forage biomass production and can affect other elements of the landscape as well.

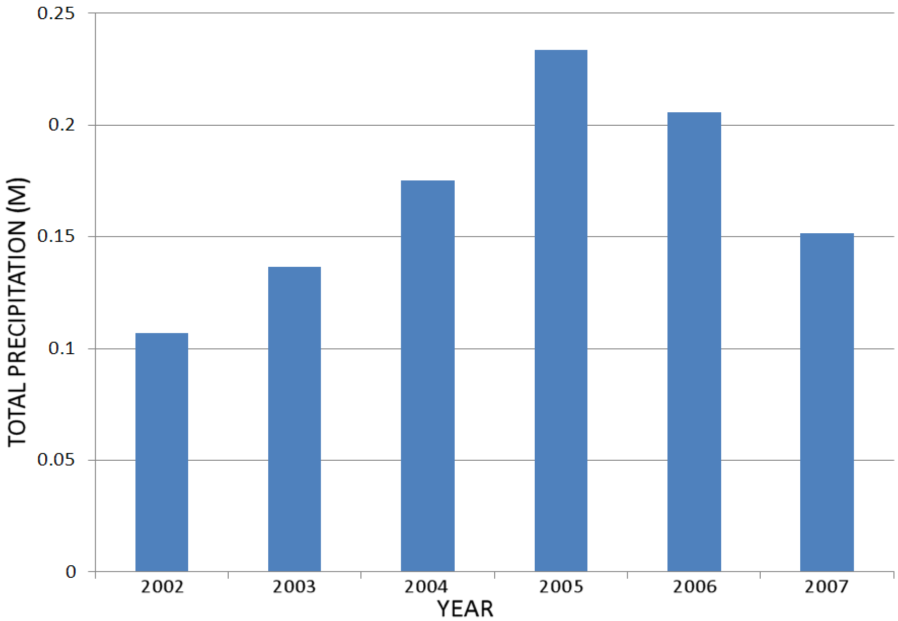

Figure 2. Accumulated precipiation from 2002 through 2007 at the O'Neal study area.

The two years selected for use in this study (2003 and 2007) represent fairly similar precipitation years. As a result, detected changes would appear to have been caused by drivers other than the environment (i.e., precipitation). This observation could help explain the poor performance seen in the 2008 forecast and also demonstrates the prominent role of precipitation as a driver variable in LULC in semi-arid ecosystems.

The use of only two data points will not capture the variability in precipitation and resulting forecasts will be no better than a simple random/chance forecast. At a minimum, future forecast models need to include annual input layers instead of only early and later images. In addition, forecast models need to be validated using a short-term prediction before basing any decisions upon longer-term forecasts.

Another source of error which could explain the poor performance of the reported forecast model was the mixed use of Landsat and SPOT imagery. Recent studies suggest that vegetation indices (NDVI) derived from one sensor are not comparable to the same index derived from another sensor (Theau et al. 2010). However, the impact of this error relative to the problems described above is probably minimal although this was not tested. Furthermore, the fact that both NDVI and MSDI layers were reclassified and scored should have helped to marginalize such errors through generalization.

CONCLUSIONS

Forecasting change in semi-arid ecosystems is challenging due to the important role played by environmental drivers such as precipitation and the highly variable nature of the same. Regardless of the modeling algorithm used (equation-based, statistical, matrix-based, system, expert, evolutionary, cellular automata, agent-based, multiple agent-based, or hybrid) future forecast models will need to take into account annual weather variables and the resulting land cover layers if accurate predictions are expected in semi-arid rangeland ecosystems.

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Notes

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