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SAGEBRUSH ECOSYSTEM CHARACTERIZATION, MONITORING, AND FORECASTING WITH REMOTE SENSING; QUANTIFYING FUTURE CLIMATE AND WILDLIFE HABITAT CHANGE

BY

COLLIN G. HOMER

A dissertation submitted in partial fulfillment of the requirements for the

Doctor of Philosophy

Geographic Information Science Center of Excellence

South Dakota State University

2013

SAGEBRUSH ECOSYSTEM CHARACTERIZATION, MONITORING, AND FORECASTING WITH REMOTE SENSING; QUANTIFYING FUTURE CLIMATE AND WILDLIFE HABITAT CHANGE

This dissertation is approved as a creditable and independent investigation by a candidate for the Doctor of Philosophy degree and is acceptable for meeting the dissertation requirements for this degree. Acceptance of this does not imply that the conclusions reached by the candidates are necessarily the conclusions of the major department.

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ABSTRACT

SAGEBRUSH ECOSYSTEM CHARACTERIZATION, MONITORING, AND FORECASTING WITH REMOTE SENSING; QUANTIFYING FUTURE CLIMATE AND WILDLIFE HABITAT CHANGE

COLLIN G. HOMER

2013

Sagebrush (*Artemisia spp.*) ecosystems constitute the largest single North American shrub ecosystem and provide vital ecological, hydrological, biological, agricultural, and recreational ecosystem services. Disturbances continue to alter this ecosystem, with climate change possibly representing the greatest future disturbance risk. Improved ways to characterize and monitor gradual change in this ecosystem are vital to its future management. A new remote sensing sagebrush characterization approach was developed in Wyoming which integrates three scales of remote sensing to derive four primary continuous field components (bare ground, herbaceousness, litter, and shrub), and four secondary components (sagebrush, big sagebrush, Wyoming sagebrush, and shrub height) using a regression tree. An independent accuracy assessment of results revealed the primary component root mean square error values ranged from 4.90% to 10.16% for 2.4-m QuickBird, 6.01% to 15.54% for 30-m Landsat, and 6.97% to 16.14% for 56-m AWiFS.

The change over time of five of these continuous field components (bare ground, herbaceous, litter, sagebrush, and shrub) was measured on the ground and by satellite across six seasons and four years to validate component change capability. Correlation of ground measurements to remote sensing predictions indicated that annual component predictions tracked ground measurements more closely than seasonal ones, and QuickBird predictions tracked ground measurements more closely than Landsat predictions. Correlation of component predictions to DAYMET precipitation revealed QuickBird components had better response to precipitation patterns than Landsat components.

Further in-depth analysis of precipitation and component change patterns was completed from 1984 to 2011 for the same five components. A statistically significant correlation model between vegetation components and precipitation was established, and used to forecast vegetation components response in 2050 using IPCC precipitation scenarios. Bare ground increased under future scenarios, with the remaining components all decreasing. When 2050 future component results were applied to sage-grouse habitat models, a loss of about 12% of nesting habitat and 4% of summer habitat were predicted to occur. Results demonstrate the successful ability of sagebrush components to characterize the sagebrush ecosystem, monitor precipitation driven gradual change, support linear models to forecast future component response, and quantify future habitat impacts on sage-grouse. **CHAPTER 1**

INTRODUCTION

Sagebrush ecosystem background

Sagebrush (Artemisia spp.) ecosystems constitute the largest North American semiarid shrub ecosystem (Anderson and Inouye, 2001) and provide vital ecological, hydrological, biological, agricultural, and recreational ecosystem services (Perfors, et al.; 2003, Connelly, et al., 2004; Davies, et al., 2007). Historically, sagebrush (Artemisia spp.) once ranged across roughly 63 million ha in the western United States and Canada, but today is among the most threatened ecosystems in North America (Knick, et al., 2003) and is undergoing further fragmentation and degradation (Connelly, et al., 2004; Schroeder, et al., 2004). The expansion of exotic plant species, altered fire frequency, intensive grazing practices, increased oil and gas development and other direct factors have altered and reduced this ecosystem (Leonard, et al., 2000; Crawford, et al., 2004; Davies, et al., 2006 & 2007) with about 50% loss in total spatial extent (Connelly, et al., 2004; Schroeder, et al., 2004; Hagen, et al., 2007). The remaining largest intact sagebrush steppe ecosystem core areas occur in Southeast Oregon, Northern Nevada, Southern Idaho, and Wyoming. Research to understand these core areas is especially important, because they represent the future of this ecosystem (Knick et al., 2003; Bradley 2010). However, constant perturbations to this system are especially disrupting vital biological services, with sagebrush habitats now the focus of major conservation efforts grappling with complex disturbance issues that cover these broad areas. Changes to this ecosystem have severely impacted the ability to provide habitats for numerous sagebrush-obligate species, including the greater sage-grouse. This has severely impacted sage-grouse populations across the species range (Connelly, et al., 2004; Garton, et al.,

2011) leaving populations threatened with extirpation in some habitats where they historically persisted (Connelly, et al., 2004; Aldridge, et al., 2008). The result is sage grouse are currently under consideration for listing as a threatened or endangered species by the U.S. Fish & Wildlife service.

Despite the impacts of past disturbances, climate change may ultimately represent the greatest future risk to this ecosystem and the services it provides (Neilson, et al., 2005; Bradley, 2010, Schlaepfer, et al., 2012A; Schlaepfer, et al., 2012B). Both warming temperatures and changing precipitation patterns (such as increased winter precipitation falling as rain) will likely favor species other than sagebrush (West and Yorks, 2006; Bradley 2010) and increase sagebrush vulnerability to fire, insects, diseases, and invasive species (McKenzie et al., 2004; Neilson, et al., 2005). Semiarid lands such as sagebrush are especially vulnerable to precipitation changes, because of low soil moisture content (Reynolds et al., 1999; Weltzin et al., 2003). Since variations in precipitation strongly influence arid and semiarid land plant composition and dynamics (Branson et al., 1976; Cook and Irwin, 1992; Pelaez et al., 1994; Ehleringer et al., 1999; Reynolds et al., 2000), a future combining greater precipitation variation with shifting precipitation events could leave the ecosystem especially vulnerable (Bradley, 2010).

Sagebrush ecosystem remote sensing monitoring

Developing adequate scientific knowledge to understand, analyze, manage, and monitor these semi-arid landscapes however, has presented a great challenge. Despite the vast area covered by this ecosystem and the numerous disturbance forces operating on the landscape, effective large area monitoring, prediction and forecasting tools have not been implemented, and widely accepted metrics to quantify and communicate disturbance magnitudes are not well developed (Booth and Tueller, 2003; West, 2003; Washington-Allen, et al., 2004; Washington-Allen, et al., 2006). Disturbance monitoring and forecasting products capable of measuring, quantifying, and reporting change in metrics understood by land managers is critical to future successful management of this ecosystem (Homer, et al., 2012; Aldridge, et al., 2008; Washington-Allen, et al., 2004; Knick, et al., 2003; Hemstom, et al., 2002).

Remote sensing has been widely recognized as the key to making ecosystem-wide analysis and disturbance monitoring successful (Booth and Tueller, 2003; Hunt Jr, et al., 2003; Tueller, 1989; Washington-Allen, et al., 2006). However, semiarid shrublands such as those containing sagebrush are difficult remote sensing environments, with discrimination challenged by sparse and similar vegetation (Graetz, et al., 1988; Laliberte, et al., 2007), which is often spectrally confounded by high proportions of bare ground, soil color, topography, and non-photosynthetic vegetation that all interfere with successful interpretation (Huang, et al., 2010, Okin and Roberts 2004). Hence, although the need for improving remote sensing application in shrublands such as sagebrush has long been recognized (Tueller, 1989), the difficulty of the challenge requires significant additional research (Forbis, et al., 2007; Knick, et al., 2003; Washington-Allen, et al., 2006). Optical remote sensing still remains the only current remote sensing data source widely available and capable of cost-effectively producing ecosystem-wide products. Improved remote sensing characterization products are needed that offer more detailed information over much larger areas, with higher accuracy and are capable of supporting monitoring at regional to local scales.

The primary source of remote sensing research in the sagebrush ecosystem has been from Landsat (Homer, et al. 2012, Sivanpillai, et al., 2009, Ramsey, et al. 2004). The multispectral capabilities and 30 meter resolution of Landsat are well suited for detecting and quantifying a range of vegetation attributes, as well as for detecting gradual change and the underlying ecological processes across large areas (Vogelmann et al., 2012). No cost Landsat data, combined with its long archival record back to 1972 with millions of images has especially made this sensor attractive (Loveland and Dwyer, 2012). However, the recent availability of higher spatial resolution sensors (e.g. QuickBird, World View 2) offer's new potential for monitoring in sagebrush ecosystems at resolutions finer than Landsat (Jakubauskas, et al., 2001; Booth and Tueller, 2003; Witztum and Stow, 2004; Mirik, et al., 2005; Homer, et al., 2012). New spectral bands at finer spatial resolution can increase the ability to detect smaller changes and improve monitoring applications. Increased sensor resolution may allow for changes to be detected at more local scales, enhancing interpretation and understanding. Also, because ground measurement approaches are often prohibitively expensive, high resolution sensors offer the potential to extrapolate ground measurement across larger areas and also provide an operational surrogate for ground plot re-measurement. However, high resolution imagery application can be hampered by high costs, limited availability and difficulty in obtaining imagery over large enough areas at the right time. Despite these limitations, high-resolution imagery will play a significant remote sensing role in

augmenting and scaling Landsat observations in the future. Studies that further explore the capabilities of these sensors to complement and support component change monitoring have yet to be completed.

Historically, remote sensing characterization of this ecosystem has been done with either general land cover classes of sagebrush over large areas (Scott, et al., 1996) or small areas with more class and structural detail (Homer, et al., 1993; Knick, et al., 1997; Ramsey, et al., 2004; Sivanpillai and Booth, 2008; Sivanpillai, et al., 2009). Change monitoring in this ecosystem using remote sensing has been limited to a few studies that have characterized abrupt types of disturbance from fire (Norton, et al., 2009; Sankey, et al., 2008), human development (Sivanpillai, et al., 2009; Thornton, et al., 1997) and some gradual types of disturbance such as grazing (Bork, et al., 1999) and climate change (Xian, et al., 2012b). However, a comprehensive understanding of the gradual changes in sagebrush ecosystem components based on remote sensing is still lacking; only a few studies have begun to explore that relationship (Ramsey, et al., 2004; Walston, et al., 2009; Baghzouz, et al., 2010; Vogelmann, et al., 2012; Xian, et al., 2012b). Remote sensing change studies have historically targeted the development of indices such as the normalized difference vegetation index (NDVI) or other similar approaches to understand change (Duncan, et al., 1993; Todd, et al., 1998; Brinkman, et al., 2011). These indices can be difficult to interpret and translate to on-the-ground understanding of sagebrush ecosystem dynamics (Hunt, et al., 2003; Coppin, et al., 2004; Gottschalk, et al., 2005).

Indices or metrics that characterize changes are needed by land managers for near real-time decisions (Hunt, et al., 2003). Fractional vegetation predictions offer an

example of products capable of supporting this type of management need. The additional capability to do long term monitoring with these components to quantify impacts on vegetation change in a sagebrush ecosystem across time would add tremendously to their value. Recent research has begun to address this concept (Xian, et al., 2012a; Xian, et al., 2012b). Approaches have centered on using a single year of training data to parameterize a base characterization layer, and then comparing several time periods to this base layer using change vector analysis to identify change, and a subsequent process to label this change (Vogelmann, et al., 2012; Xian, et al., 2012a; Xian, et al., 2012b). This approach typically assumes areas identified in the change vector process can be labeled using values from the base characterization layer. For example, Xian, et al. (2012a), used a 2006 sagebrush component base characterization layer developed with training from 2006 to project sagebrush component change back to two years (1996 and 1988) using a change vector approach to identify change, and regression tree analysis to label the change. Although this is a promising approach, no research has tested the assumptions of this concept using repeated ground-based measurements over many time steps (seasons or years) to fully evaluate the ability of the change vector approach to detect fine scale change within sagebrush ecosystems.

Climate change detection and forecasting

A sagebrush ecosystem remote sensing monitoring approach needs to be capable of detecting climate induced change (Xian, et al., 2012, Bradley 2010, Neilson, et al., 2005). Remote sensing images that can be interpreted into fractional ecosystem components offer a way to quantify and regionalize subtle climate process impacts on vegetation change in a sagebrush ecosystem across time (Xian et al., 2012A; Xian et al., 2012B). Specifically, information about long term variations of sagebrush ecosystem components can be used to determine the potential relationship between magnitudes of component change and the regional climate. The release of DAYMET Daily Gridded Surface Climate Data, (Thornton, et al., 1997) providing daily precipitation data at a 1-km spatial resolution, provides a new opportunity to explore potential finer scale links of climate change to observed ecosystem change. For example, historical relationships can potentially be developed using the long temporal remote sensing records of Landsat, and the corresponding DAYMET precipitation records to explore linkage between climate change and measured ecosystem change.

Once the historical relationship of component change and precipitation change is modeled, scenarios of future change can be developed using future precipitation projections. Advances in climate forecasting continue to evolve with the use of atmospheric general circulation models (GCMs). These models provide future precipitation forecasts, which can be implemented in future component change scenarios. However, since GCMs are produced at very coarse spatial resolutions (e.g a few hundred kilometers per cell) they require downscaling for successful regional application (Tabor and Williams 2010; Fowler et al., 2007). Because shifts in precipitation may have a greater impact on ecosystem dynamics than rising CO₂ or temperature (Weltzin et al., 2003), downscaled GCMs that accommodate regional processes (e.g., land-water interactions and topography) are especially important when modeling semiarid systems such as sagebrush. Future precipitation scenario models from the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2007) provide one credible source of future precipitation scenarios. The ability to convert future IPCC precipitation quantities to corresponding magnitudes of future component change would provide an important advancement for understanding the potential impacts of climate change in this ecosystem.

Wildlife habitat applications

An important step beyond future component climate scenario development, is translating component change impacts to specific wildlife habitat issues. Such a step would offer critical benefit for habitat managers, since successful wildlife management in the future will need the ability to predict the impacts of climate change on species habitat and populations (U.S. Fish and Wildlife Service 2013, Nielson et al., 2005). One example is the greater sage grouse, a species under current consideration for potential listing as a threatened or endangered species. Because sage grouse are completely dependent on the sagebrush ecosystem, their habitat needs provide a good target for remote sensing component testing. Sage-grouse experts recognize the need for quantitative monitoring of habitat trends and emphasize the importance of reducing uncertainty about climate change impacts on their habitat (U.S. Fish and Wildlife Service, 2013). Extensive sage grouse seasonal habitat models have been recently developed using remote sensing components (Fedy et al., 2013) providing an ideal opportunity to test if potential future habitat impacts can be quantified from changing precipitation.

Research goals and hypothesis questions

The overall goal of this research was to define, develop, and test a large-area sagebrush ecosystem characterization, monitoring, and future prediction system based primarily upon remote sensing. This research was strategically focused in the state of Wyoming, an important core area of the sagebrush ecosystem where answers to these research questions are critically needed to address increasing resource conflicts from multiple driving forces. This research was guided by four primary hypotheses, including:

1) Characterization of sagebrush ecosystem components using remote sensing continuous field predictions can provide useful land management relevant information at improved mapping accuracies.

2) The majority of annual and seasonal change observed in sagebrush ecosystem components through ground measurement can be replicated using remote sensing based continuous field component measurements.

 Annual and seasonal sagebrush ecosystem continuous field component change derived from remote sensing is significantly related to corresponding precipitation change.

4). Linear models developed from correlating historical responses of sagebrush ecosystem continuous field components to historical trends in precipitation variation can support quantification of feasible future sagebrush continuous field component and habitat change scenarios using future precipitation forecasts.

Research results provide answers about the accuracy at which sagebrush continuous field components can be characterized with remote sensing, the magnitudes of changes that can be detected annually and seasonally, the ability to forecast these changes into the future based on precipitation projections, and the magnitudes of sage grouse habitat change that can be expected with these future forecasts.

Summary of chapters

Chapter 2 examines the need for improving the remote sensing characterization of the sagebrush ecosystem over areas large enough to provide ecosystem analysis, but with enough detail to support local resource management and change monitoring. A series of sagebrush ecosystem continuous field components (four primary and four secondary components) were developed at three spatial scales to test the potential for characterization improvement. A rigorous accuracy assessment was performed to quantify the accuracy and the magnitude of improvement over existing remote sensing categorical classifications. This chapter addresses research hypothesis one, and was published in the *International Journal of Applied Earth Observation and Geoinformation*.

Chapter 3 explores the ability of remote sensing derived sagebrush ecosystem continuous field components to monitor seasonal and annual change, and test if that change is related to changing precipitation. This was achieved by monitoring sagebrush components across four years and six seasons using two spatial scales of satellite imagery and performing coincident ground-based vegetation sampling. Precipitation data covering the same period were then correlated to annual and seasonal component change. This chapter addresses research hypothesis questions two and three, and was published in the *Journal of Applied Remote Sensing*.

Chapter 4 examines the historical relationship between changing precipitation and changing sagebrush continuous field component values over 28 years (1984-2011), and tests whether that relationship can be developed into a model. This chapter further explores if such a model can be applied to see if future component change can be predicted in 2050 using future precipitation forecasts. 2050 future component predictions are also assessed for change impacts to sage-grouse seasonal nesting and summer habitat from a 2006 baseline. This chapter further addresses research hypothesis three and also addresses research hypothesis four. This chapter was submitted for publication to the *Journal of Ecological Indicators*.

Chapter 5 provides an overall synthesis of the results and summarizes the research hypothesis findings. The significance of the research results is also reviewed and recommendations for future research are presented.

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CHAPTER 2

MULTI-SCALE REMOTE SENSING SAGEBRUSH CHARACTARIZATION WITH REGRESSION TREES OVER WYOMING, USA; LAYING A FOUNDATION FOR MONITORING

Homer, Collin G., Aldridge, Cameron A., Meyer, Debra K., and Spencer Schell. 2012. *International Journal of Applied Earth Observation and Geoinformation*, 14, 233-244.

Abstract

Sagebrush ecosystems in North America have experienced extensive degradation since European settlement. Further degradation continues from exotic invasive plants, altered fire frequency, intensive grazing practices, oil and gas development, and climate change - adding urgency to the need for ecosystem-wide understanding. Remote sensing is often identified as a key information source to facilitate ecosystem-wide characterization, monitoring, and analysis; however, approaches that characterize sagebrush with sufficient and accurate local detail across large enough areas to support this paradigm are unavailable. We describe the development of a new remote sensing sagebrush characterization approach for the state of Wyoming, U.S.A. This approach integrates 2.4-m QuickBird, 30-m Landsat TM, and 56-m AWiFS imagery into the characterization of four primary continuous field components including percent bare ground, percent herbaceous cover, percent litter, and percent shrub, and four secondary components including percent sagebrush (Artemisia spp.), percent big sagebrush (A. tridentata), percent Wyoming sagebrush (A. t. Wyomingensis), and shrub height using a regression tree. According to an independent accuracy assessment, primary component root mean square error (RMSE) values ranged from 4.90% to 10.16% for 2.4-m QuickBird, 6.01% to 15.54% for 30-m Landsat, and 6.97% to 16.14% for 56-m AWiFS. Shrub and herbaceous components outperformed the current data standard called LANDFIRE, with a shrub RMSE value of 6.04 versus 12.64 and a herbaceous component RMSE value of 12.89 versus 14.63. This approach offers new advancements in sagebrush

characterization from remote sensing and provides a foundation to quantitatively monitor these components into the future.

1. Introduction

Sagebrush (*Artemisia* spp.), the most common semiarid vegetation type in North America, once ranged across roughly 63 million ha in the western United States and Canada, but today it is among the most threatened ecosystems in North America (Knick, et al., 2003) and is undergoing further fragmentation and degradation (Connelly, et al., 2004; Schroeder, et al., 2004). The expansion of exotic plant species, altered fire frequency, intensive grazing practices, increased oil and gas development, climate change, and other factors continue to impact sagebrush ecosystems (Aldridge, et al., 2008; Connelly, et al., 2004; Knick, et al., 2003). Coordinated ecosystem-wide analysis, integrated with monitoring and management activities, is needed to better maintain and understand the ecology and functioning of sagebrush ecosystems (Hemstrom, et al., 2002), of which remote sensing could play a critical role (Tueller, 1989; Booth and Tueller, 2003; Hunt Jr, et al., 2003; Washington-Allen, et al., 2006).

However, semiarid shrublands such as those containing sagebrush are difficult remote sensing environments, with discrimination made difficult by sparse and similar vegetation (Graetz, et al., 1988; Laliberte, et al., 2007), which is often spectrally confounded by high proportions of bare ground, soil color, topography, and nonphotosynthetic vegetation that all interfere with successful interpretation (Huang, et al., 2010). Hence, although the need for improved remote sensing accuracy and detail in shrublands has been recognized (Tueller, 1989), much progress remains to be made (Forbis, et al., 2007; Knick, et al., 2003; Washington-Allen, et al., 2006).

Historically, optical satellite remote sensing has been used to characterize either general land cover classes of sagebrush over large areas (Scott, et al., 1996) or small spatial areas with more class and structural detail (Homer, et al., 1993; Knick, et al., 1997; Ramsey, et al., 2004; Sivanpillai and Booth, 2008; Sivanpillai, et al., 2009). However, for successful ecosystem-wide analysis and management, new products are needed that offer more detailed information over much larger areas and are also capable of supporting monitoring. Only one large U.S. national effort to date, the Landscape Fire and Resource Management Planning Tools Project (LANDFIRE), has attempted a more detailed sagebrush characterization over large areas (Rollins, 2009). Results may be adequate for intended National planning applications but are inadequate for other desired wildlife, range management, and climate change applications.

Optical remote sensing is the only current data source capable of cost-effectively producing ecosystem-wide products. Hence, our research seeks to further develop optical remote sensing characterization of sagebrush lands over areas large enough to provide ecosystem analysis, but with enough detail to support local adaptive resource management and change monitoring. We concluded this goal was best accomplished by the classification of a series of multiple continuous field components (four primary and four secondary components) at three spatial scales. Consequently, our research focused on deriving a method to propagate high quality field-based sampling through multiple scales of imagery in order to improve large regional component-based classifications. Steps included (1) integrating the collection of ground-measured plot data coincident with the acquisition of 2.4-m resolution imagery; (2) predicting ground-measured plot data across 2.4-m images for extrapolation on coarser imagery; (3) acquiring multiple seasons of imagery at two additional spatial scales (30 m and 56 m) for large area characterization; (4) using regression tree technology for prediction; and (5) performing rigorous accuracy assessment of component predictions.

2. Study Area

Wyoming is a large, sparsely populated state in the western United States with an area of over 253,000 km². It contains large tracts of contiguous sagebrush lands, with an estimated 24% of all sagebrush within the U.S. Intermountain region (Connelly, et al., 2004) (Fig. 1). Topographic position and exposure combined with elevation (ranging from 969 m to 4,207 m) are the major determinants of plant distribution patterns (Knight, 1994).

Our research focused on elevations below 2,377 m, on areas dominated by sagebrush shrubland intermingled with salt desert shrubland and grassland containing a wide variety of species. Sagebrush species include both taller and shorter growth forms, but all display a characteristic gray appearance, have relatively low chlorophyll concentrations, and typically retain their leaves year-round. Big sagebrush (*Artemisia tridentata*) is by far the most abundant sagebrush in Wyoming, other common species include black sagebrush (*A. nova*), silver sagebrush (*A. cana*), and low sagebrush (*A. arbuscula*) (Knight, 1994).



Fig. 1. Extent of landscapes targeted for development of component models for the state of Wyoming (brown). White areas represent areas excluded from analysis. Red lines indicate Landsat path/row boundaries, and green squares represent numbered QB collection sites used for training both Landsat and AWiFS imagery. AWiFS imagery covered the complete extent of the state.

3. Materials and Methods

We developed methods to integrate 2.4-m QuickBird (QB) imagery, 30-m

Landsat Thematic Mapper (TM) imagery, 56-m Indian Remote Sensing Satellite

Advanced Wide-Field Sensor (AWiFS) imagery, and extensive ground sampling to

develop continuous field predictions with a regression tree (RT) (e.g., the percentage of

the cell or pixel covered by the class viewed from overhead) for eight sagebrush

ecosystem components (hereafter referred to simply as components). These include four primary components of percent bare ground, percent herbaceous cover (grass and forb), percent shrub, and percent litter and four secondary components nested within the shrub component of percent sagebrush (*Artemisia* spp.), percent big sagebrush (*A. tridentata*, representing three subspecies), percent Wyoming sagebrush (*A. tridentata wyomingensis*), and mean shrub height (centimeters). A summary of methodological approaches is presented in Table 1, with details listed below by project objective.

Table 1. Summary of multiple scale model prediction procedures for Wyoming.



3.1 QB image preparation

A total of 30 QB images (64 km² each) were selected to support and develop regression tree predictions for nine Landsat TM path/rows and one AWiFS path/row across Wyoming (Fig. 1). QB images were specifically selected to span a reasonable range of landscape diversity for each Landsat path/row. QB image location criteria included 1) representative ecological and spectral characteristics of the entire TM path/row, 2) adequate public land and road access for sampling, 3) good spatial distribution on the TM path/row, and 4) ability to represent multiple path/rows in overlap areas to facilitate edge-matching and optimize training data utilization. QB images were collected and sampled over two years, with 13 images completed in 2006 for three TM path/rows and 17 images completed in 2007 for six TM path/rows.

In order to identify homogeneous sites for potential field sampling, we used Definiens eCognition¹ software (Baatz, et al., 2003) to segment the QB imagery into image objects (Homer, et al., 2009). Each QB image was also per-pixel classified into 30 unsupervised clusters using an isodata algorithm in Leica Geosystems ERDAS¹ Imagine software using all four spectral bands; previous clustering trials had determined 30 clusters typically approximated the degree of spectral discrimination sufficient for our approach. Segmented polygons were then intersected with the 30 clusters to identify the majority cluster class for each polygon and essentially capture the full potential range of spectral variability across the QB image for sampling selection. Typically, two sampling polygons from each of the 30 cluster classes were selected for a minimum of ~60 sample

¹ The use of any trade, product or firm name is for descriptive purposes only and does not imply endorsement by the U.S. Government.

polygons per QB image. To optimize field sampling while still capturing spectral and ecological diversity, selected polygons were further identified based on the size of the patch (> 0.5 hectare), adjacency to roads (within 1 km), land ownership access, and spatial distribution on the image (no clumping). Ground sampling was completed as near to the QB acquisition date as logistically possible. If the QB image was not acquired prior to the scheduled field sampling, we applied selection procedures using 2006 1-m National Agricultural Imagery Program (NAIP) data, which were adequate for segmentation but inadequate for the modeling and prediction methods which required QB.

3.2 Field sampling protocols

Once polygons were selected within a QB image, we sampled vegetation characteristics using ocular estimation (Daubenmire, 1959; Knick, et al., 1997; Mirik, et al., 2007; Sant, 2005) at 14 1-m² quadrats along two 30-m transects within each polygon plot (Homer, et al., 2009). This design facilitated quick measurement (and future remeasurement) of component abundance. For each of 14 quadrats, we estimated cover from an overhead perspective (satellite), with the total cover of all vegetation and soil components summing to 100%. Shrubs and trees were identified to the species level, except for sagebrush, which was measured at the subspecies level. All other components within the quadrat were combined into broad categories of herbaceous vegetation, litter, and bare ground. Cover measurements for shrubs were primarily based on portions of the canopy with live green vegetation. Cover measurements for herbaceous vegetation combined cover of dead standing woody vegetation and detached plant and animal organic matter. Bare ground included any exposed soil or rocks. All individual quadrat cover estimates were made in 5% increments. We estimated the height of each shrub or tree species by measuring the height of the tallest green vegetation (excluding seed stalks) for one representative plant within each quadrat. Because sampling teams included multiple individuals, both initial training and subsequent quality assurance oversight was instituted to maintain sampling consistency.

For application to remotely sensed data, we defined each plot as the polygon enclosed by connecting the start and end points of both transects (~0.06 ha in area, Fig 2). We calculated a mean value for each of the eight components based on the average of all $14 \ 1-m^2$ quadrats within the plot. This mean value was then assigned to all QB pixels occurring within the plot. Within plot pixel spectral values were then evaluated, and pixels > ± one standard deviation from the mean spectral value were removed from training consideration as anomalous outliers. This resulted in a more robust training data pool and increased model prediction accuracy at the QB level. Additionally, for some small QB heterogeneous areas our larger transects were not appropriate, and supplemental non-standardized micro-plots measured with fewer sample frames over a condensed area were used to better capture the full range of component conditions. Sample plots where spectral values were contaminated by clouds or cloud shadows were also removed from the QB model training dataset.

3.3 QB image predictions

We modeled eight components from QB images using a regression tree algorithm called Cubist² (Quinlan, 1993). Typically, all four 2.4-m spectral bands (Band 1 visible blue, 0.45–0.52 μ m; Band 2 visible green, 0.52–0.60 μ m; Band 3 visible red, 0.63–0.69 μ m; and Band 4 near infrared, 0.76–0.90 μ m) were used directly, with an additional three bands of ratio indices targeted for capturing Green NDVI (Band 4 – Band 2)/(Band 4 + Band 2), Moisture (Band 4 – Band 1)/(Band 4 + Band 1), and Leaf Area (Band 4)/(Band 3 + Band 2) for a total of seven spectral inputs. We developed training inputs for each component using the average component value, calculated from the aggregated quadrat measurements, within each sample plot (excluding outliers) within each QB image (typically 60 sample plots, Fig. 2). Sub-shrub secondary components were restricted to occur only in shrub areas by post-modeling masking with the shrub component. Predictions of the per-pixel percent cover for seven components as a continuous variable from 0 to 100% and shrub height (cm) were then spatially extrapolated for all pixels in each QB image.

3.4 Landsat imagery predictions

We modeled eight components using Landsat TM multi-season imagery across nine path/rows. For each component, we averaged predictions for all of the QB 2.4-m pixel values within a 30-m TM cell to create a mean rescaled value for training (Fig. 2). We then filtered 30-m cell training data by summing the four independently modeled primary components (bare ground, shrub, herbaceous, and litter) and removing cells that failed the target summation threshold of > 90% or < 110% judging them inadequate for

² The use of any trade, product or firm name is for descriptive purposes only and does not imply endorsement by the U.S. Government.

training application. Thirty QB images were used to train the nine TM path/rows (Fig. 1) ranging from 4 to 8 QB images for each TM path/row.

To ensure adequate data availability across the state, in some cases we combined both 2006 and 2007 training and image information. An evaluation to compare crossyear phenology issues for path/row 37/31 indicated combining training data from both



Wyoming during 2006-2007. RT component models at all scales were ultimately extrapolated from 1-meter quadrat field measurements.

years increased RMSE error an average of 0.28 for more invariant components (shrub and sagebrush cover) and 1.3 for more variant components (bare ground and herbaceous cover). We felt this was acceptable and QB predictions from both years were combined to build training data for Landsat modeling. Further, precipitation was similar for both years, suggesting similar plant growth in both years (Wyoming State Climate Office, 2010). Approximately 40 input data layers based on multiple image dates, image band ratios, ratio differences between image dates, and 30-m ancillary topographic data derived from the National Elevation Dataset were used to build RT model predictions (Table 2). Three TM dates for each path/row were selected to represent early, middle, and late growing season conditions. All Landsat images were standardized to at-satellite reflectance before their use in the RT (Chander, et al., 2009).

We created training data proportions to weight the RT to better address the full range of training data. We divided training data for each of the eight component predictions into three roughly equal bins based on the mean and original RMSE of training data values derived from cross-validation. Values less than the mean minus RMSE were grouped into a low bin, values greater than the mean plus RMSE were grouped into a high bin, and the remaining values were considered the middle bin. This approach ensured that higher and lower component predictions carried more equal weighting in model development and reduced overall bias (Wylie, et al., 2008). We extrapolated predictions for all seven cover components from 0 to 100% and shrub height across all Landsat pixels by path/row (a total of 72 separate regression tree models). Subshrub secondary components were restricted to occur in shrub-only areas by postmodeling masking with the shrub component. Landsat individual scene results were edge-matched into a single mosaicked product by manually following land features and masked areas to create the smoothest possible transition between individual predictions.

Table 2. Component prediction data input by sensor. This represents the total data made available to the regression tree for prediction¹.

Landsat Based Predictions

Imagery, original bands

Landsat TM, Band 1, spring, summer and fall dates Landsat TM, Band 2, spring, summer and fall dates Landsat TM, Band 3, spring, summer and fall dates Landsat TM, Band 4, spring, summer and fall dates Landsat TM, Band 5, spring, summer and fall dates Landsat TM, Band 7, spring, summer and fall dates 3 Ratio Index, Band 1, spring, summer and fall dates 3 Ratio Index, Band 2, spring, summer and fall dates 3 Ratio Index, Band 3, spring, summer and fall dates Ratio Diff. Index, Band 1, spring, summer and fall Ratio Diff. Index, Band 2, spring, summer and fall Ratio Diff. Index, Band 3, spring, summer and fall Ratio Diff. Index, Band 3, spring, summer and fall

Ancillary data

Aspect, 9 Direction

Elevation, Thematic classes

Slope Position Index

Slope, Degrees

¹Landsat ratios found to be most effective included Green NDVI (Band 4 – Band 2)/(Band 4 + Band 2), Moisture Index (Band 4 – Band 5)/(Band 4 + Band 5), and a Specific Leaf Area Index (Band 4)/(Band 3 + Band 7). AWiFS ratios included Green NDVI (Band 3 – Band 1)/(Band 3 + Band 1), Moisture Index (Band 3 – Band 4)/(Band 3 + Band 4), and a Specific Leaf Area Index (Band 3)/(Band 2 + Band 4). The ratio differences index for both sensors was calculated by differencing ratio derivatives between paired seasonal dates. Ancillary data were derived from the 30-m National Elevation Dataset.

AWiFS Based Predictions

Imagery, original bands

AWiFS, Band 1, spring and fall dates AWiFS, Band 2, spring and fall dates AWiFS, Band 3, spring and fall dates AWiFS, Band 4, spring and fall dates 3 Ratio Index Band 1, spring/fall dates 3 Ratio Index Band 2, spring/fall dates 3 Ratio Index Band 3, spring/fall dates Ratio Diff. Index, Band 1, spring/fall Ratio Diff. Index, Band 2, spring/fall Ratio Diff. Index, Band 2, spring/fall Ratio Diff. Index, Band 3, spring/fall Ancillary data Aspect, 9 Direction Elevation, Thematic classes Slope Position Index

Slope, Degrees

Localized remodeling of data across edge-matching boundaries was required in two small instances where the predictions were very different and required targeted models to resolve these differences.

3.5 AWiFS imagery predictions

We modeled all eight components using two seasons of AWiFS imagery across the state of Wyoming. Four separate dates in June were required to complete a 2006 June cloud-free mosaic for the state, with September requiring only one AWiFS date. No statewide cloud-free July image was available, so this date was eliminated from model development. Because of the large spatial area a single AWiFS scene covers, only a single scene from each season was required for the base image. Subsequently, we determined that the images available in standard digital number format did not need to be corrected to at-satellite reflectance. We used component predictions from the QB images and rescaled them from 2.4-m cells to 56-m cells for AWiFS to provide training data for the model predictions. All 30 QB images were used to train the AWiFS predictions. QB training data were manipulated similar to the Landsat method above. The combination of input layers used to derive model results (approximately 21 input layers for AWiFS) predictions) is represented in Table 2. These input layers represent the total data made available to the RT for data mining to build model predictions for each component. Prediction, extrapolation, and accuracy assessment protocols follow the Landsat methods.

3.6 Model Evaluation

Component models were evaluated in four different ways including crossvalidation, independent accuracy assessment, summation testing, and LANDFIRE product comparison. Initial model evaluation was performed using a 10-fold crossvalidation from the Cubist RT. Accuracy estimates were derived by using each subset to evaluate the classification developed using the remaining training samples, and their average value represents the accuracy of the classification developed using all reference samples.

An accuracy assessment was performed for the 17 QB images collected and sampled in 2007, using 12–15 extra plots collected from each image for independent evaluation of QB model predictions. Evaluation plots were selected from all sampled plots by targeting spectral categories (30 per image) that contained excess plots beyond the two required for model training. For Landsat and AWiFS accuracy assessment, we used independent plot samples collected across all TM path/rows during both years. To optimize field crew access, sample locations for component assessment were restricted to landscapes below 2,377 m in elevation, on public land, within 1 km of a mapped road or trail, and within the extent of the lumped shrub, grass, and barren classes in the U.S. National Land Cover Database (NLCD 2001) (Homer, et al., 2007). Independent plot selection for 2007 included initial landscape stratification using a random selection of 5km circles, located across three site potential strata (high, medium, and low), (Wylie and Rover, 2008) that spanned potential sagebrush ecosystem situations from barren land to denser shrublands. Once initial selection was complete, a second stage random sample of eight plot locations was placed within the 5-km circle, stratified across the same site potential classes. Both 2006 and 2007 independent plot samples were combined for this assessment. Plot sampling for both years was completed using the same field protocols

used for training plot collection. In order to provide an additional means of component comparison, NDVI was calculated for each sensor from the leaf-on date and regressed against independent plots to illustrate the typical photosynthetic signal available for component prediction.

Independent accuracy assessment results are reported using the coefficient of determination (R²), the RMSE, the normalized root mean square error (NRMSE), and a linear weighted Kappa. RMSE represents an absolute measure of model fit and is in the same unit as the modeled variable (Xu, et al., 2005). NRMSE is dimensionless and is calculated by dividing the RMSE by the range of observed values to allow comparisons among different RMSE calculations and is typically expressed as a percentage. Kappa statistics were calculated for primary components using the linear weighting approach (designed for ordinal categories) to help understand error distribution within component predictions. Categories for kappa calculation were formed by grouping bare ground and herbaceous components into 10 intervals of 10% each, and litter and shrub into 10 intervals of 5% each. Litter and shrub had smaller data ranges and required 5% intervals to approximately match the number of categories created for bare ground and herbaceousness. Cross-validation and NDVI accuracy assessment results are reported using only the coefficient of determination.

An additional measure of model robustness was determined by the summation of the four primary cover components, which though created independently should ideally sum to 100% in pure rangeland areas. In order to have only pure rangeland cells evaluated, NLCD tree canopy and land cover products were used to identify and mask out potential partial rangeland pixels that contained trees or other non-rangeland content such as agriculture.

The final test of model robustness compared the results of our shrub and herbaceous component predictions to published LANDFIRE data shrub and herbaceous pixel predictions (circa 2001). The median value from the discrete 10% interval class bins for both LANDFIRE shrub and herbaceous predictions were used for comparison.

4. Results

4.1 Component predictions

A total of 2,304 field plots were sampled during the summers of 2006 and 2007 across Wyoming. Of these, 1,780 were used for modeling 240 component predictions across 30 QB images, 227 were withheld from model development to test subsequent QB predictions, and 297 plots were specifically sampled for model validation of the Landsat and AWiFS predictions. Using field plots, we modeled predictions for eight components for 30 2.4-m QB 64-km² image extents (overall 240 RT models), for 30-m Landsat across nine path/row extents (overall 72 RT models), and for 56-m AWiFS across all of Wyoming (overall 8 RT models) (Fig. 1). AWiFS predictions were used to supplement areas outside of modeled Landsat predictions to complete an entire state coverage (Fig. 3).

Component product distributions reveal bare ground with the broadest overall range and most even distribution, followed by herbaceousness and litter, which both still exhibit fairly wide ranges and distributions, especially compared to shrub (Fig. 4). Shrub and corresponding secondary components exhibit a much more compressed range and uneven distribution, with Wyoming sagebrush having the most limited range.

small portions of the state not covered by the Landsat path/rows displayed in Fig. 1. AWiFS predictions. AWiFS predictions were resampled to Landsat scale (30 m) and inserted in Fig. 3. Wyoming statewide predictions for bare ground and shrub from combined Landsat and





Fig. 4. Primary, secondary, and shrub height component histogram distributions for Wyoming-wide 30-m predictions.

4.2 Cross-validation and Independent Accuracy Assessment

QB prediction accuracy varied by component and QB image. Overall, model cross-validation resulted in an average R^2 value across all components of 0.71, with values ranging from 0.65 for Wyoming sagebrush to 0.78 for bare ground. Independent validation results derived from the 227 field plots withheld from modeling resulted in an average R^2 value across all components of 0.51, with R^2 values ranging from 0.38 for Wyoming sagebrush to 0.71 for bare ground; all correlations were significant at P < 0.01. By contrast, regression of QB NDVI against field plots averaged an R^2 value of 0.18. Based on the independent evaluation, RMSE values averaged 6.52 and ranged from 4.76 for sagebrush to 10.16 for bare ground (Table 3). NRMSE values across primary component QB predictions averaged 13% (Table 3).

Landsat and AWiFS prediction accuracy varied by individual component and image path/row, and were typically more variable then QB results. Landsat model crossvalidation resulted in an overall average R² value across all components of 0.80, with values ranging from 0.73 for shrub to 0.87 for bare ground. Independent Landsat validation results derived from 297 independently sampled field plots resulted in an average R² value across all components of 0.26, with R² values ranging from 0.14 for herbaceous to 0.46 for bare ground with all correlations significant at P <= 0.01 (Fig. 5). By contrast, regression of Landsat NDVI against field plots averaged an R² value of 0.09. Based on the independent evaluation, RMSE values overall average 8.97 and ranged from 5.46 for sagebrush to 15.54 for bare ground. NRMSE values for Landsat primary

predictions averaged 16, three higher than QB.

Table 3. Statewide model cross-validation and accuracy assessment results for seven cover components and one height component by sensor. Root mean square error (RMSE) values are in the units of model prediction (percent or height). Normalized root mean square error (NRMSE) values are expressed in percent of the total value range. NDVI results are derived from using a single date leaf-on image.

Sensor	Modeled Variable	Model Cross- validation	Independent Validation Plots						
		Mean - R ²	N	R²	RMSE	NRMSE	NDVI R²		
QuickBird	Bare Ground (%)	0.78	229	0.71	10.16	0.11	0.47		
QuickBird	Herbaceous (%)	0.74	229	0.42	6.60	0.11	0.19		
QuickBird	Litter (%)	0.67	229	0.57	7.93	0.11	0.27		
QuickBird	Shrub (%)	0.68	229	0.53	4.90	0.13	0.14		
QuickBird	Sagebrush (%)	0.71	229	0.52	4.76	0.14	0.06		
QuickBird	Big sagebrush (%)	0.70	229	0.44	4.99	0.15	0.05		
QuickBird	Wyomingensis (%)	0.65	213	0.38	4.90	0.14	0.001		
QuickBird	Shrub height (cm)	0.76	229	0.53	7.95	0.11	0.24		
QuickBird	Mean	0.71	227	0.51	6.52	0.13	0.18		
Landsat	Bare Ground (%)	0.87	297	0.46	15.54	0.16	0.23		
Landsat	Herbaceous (%)	0.79	297	0.14	12.96	0.17	0.14		
Landsat	Litter (%)	0.83	297	0.22	9.34	0.16	0.20		
Landsat	Shrub (%)	0.76	297	0.28	6.01	0.15	0.01		
Landsat	Sagebrush (%)	0.81	297	0.33	5.46	0.17	0.002		
Landsat	Big sagebrush (%)	0.81	297	0.31	5.63	0.17	0.000		
Landsat	Wyomingensis (%)	0.79	297	0.18	5.66	0.17	0.004		
Landsat	Shrub height (cm)	0.73	297	0.15	11.20	0.17	0.09		
Landsat	Mean	0.80	297	0.26	8.97	0.16	0.09		
AWiFS	Bare Ground (%)	0.81	297	0.31	16.14	0.16	0.12		
AWiFS	Herbaceous (%)	0.83	297	0.10	11.81	0.16	0.02		
AWiFS	Litter (%)	0.66	297	0.18	9.67	0.16	0.08		
AWiFS	Shrub (%)	0.62	297	0.09	6.97	0.18	0.07		
AWiFS	Sagebrush (%)	0.56	297	0.15	6.11	0.19	0.05		
AWiFS	Big sagebrush (%)	0.59	297 0.11 6.66 0.20				0.04		
AWiFS	Wyomingensis (%)	0.64	297	0.08	6.28	0.19	0.01		
AWiFS	Shrub height (cm)	0.52	297 0.18 10.18 0.16 0.04						
AWiFS	Mean	0.65 297 0.15 9.23 0.18 0.0							



Fig. 5. Scatterplots representing the correlation between field measurements and Landsat predictions for all four primary components across Wyoming. These are based on the 297 independent field samples used for validation.

AWiFS component prediction accuracy was more variable than either Landsat or QB (Table 3). AWiFS initial model cross-validation resulted in an average R^2 value across all components of 0.65, with values ranging from 0.52 for shrub to 0.81 for bare ground. Independent AWiFS validation resulted in an average R^2 value across all components of 0.15, with R^2 values ranging from 0.08 for Wyoming sagebrush to 0.31 for bare ground with all correlations significant at P <= 0.01 (Table 3). Regression of

AWiFS NDVI against field plots averaged an R^2 value of 0.05. Based on the independent evaluation, RMSE values overall averaged 9.23 and ranged from 6.11 for sagebrush to 16.14 for bare ground. NRMSE values for the AWiFS primary predictions averaged 18, two higher than Landsat (Table 3).

Kappa values generated for the four primary statewide Landsat/AWiFS components after they were categorized ranged from a high of .38 for bare ground to a low of .14 for herbaceousness (Table 4). Bare ground had the widest range with values between 10 and 100%, herbaceous values had the next widest range with values between 10 and 80%, and shrub and litter values were between 5 and 40% (Fig. 6).

	Linear Weighted	Standard	0.95 Confidence				
	Kappa	Error	Lower Limit	Upper Limit			
Bare Ground	0.383	0.031	0.315	0.438			
Herbaceous	0.140	0.048	0.047	0.233			
Litter	0.288	0.035	0.220	0.357			
Shrub	0.307	0.035	0.240	0.375			

Table 4. Kappa values for categorized interval comparison of the four primarycomponent predictions against independent validation plots.

	Bare	Gr	oun	d									_	Herb	ace	ous	;								
					Fie	eld Da	ita % (Class					Г					Fie	ld Dat	ta % C	lass				
		10	20	30	40	50	60	70	80	90	100	total			10	20	30	40	50	60	70	80	90	100	total
	10	2	1	1	0	0	0	0	0	0	0	4		10	76	12	2	1	1	0	0	0			92
	20	0	0	1	1	2	1	0	0	0	0	5		20	99	33	12	0	0	0	0	0			144
Class	30	1	0	1	1	2	1	2	0	0	0	8	lass	30	28	9	2	0	0	1	0	0			40
%	40	0	3	2	5	8	7	5	5	1	0	36	8	40	6	5	0	0	0	0	0	0			11
ction	50	0	1	2	4	4	10	19	7	1	0	48	ction	50	2	0	0	0	0	0	0	0			2
redi	60	0	0	1	1	6	17	16	13	6	0	60	redi	60	2	0	3	0	0	0	0	0			5
Ē	70	0	0	0	1	1	10	21	27	4	0	64	4	70	0	0	1	0	0	1	0	0			2
	80	0	0	0	0	0	4	12	21	24	2	63		80	0	0	0	0	0	0	0	1			1
	90	0	0	0	0	0	0	0	2	4	3	9		90		_									
	100	0	0	0	0	0	0	0	0	0	0	0		100						e					
	total	3	5	8	13	23	50	75	75	40	5	297		total	213	59	20	1	1	2	0	1			297
	Litte	r											_	Shru	ıb										
					Fie	eld Da	nta % (Class					Field Data % Class												
		5	10	15	20	25	30	35	>40			total			5	10	15	20	25	30	35	>41	0		total
	5	7	2	4	0	0	0	0	0			13		5	28	10	6	1	0	0	0	0		_	45
5	10	13	21	13	13	3	3	0	2	2	2 - 2	68	0	10	52	47	19	5	1	0	0	0			124
Class	15	8	15	14	14	11	2	0	0	<u></u>	-0-0	64	Clas	15	8	24	23	11	8	0	1	0	-6		75
%	20	3	19	14	14	15	3	2	3			73	%	20	3	11	13	5	5	3	0	0		_	40
ctior	25	2	0	7	8	10	4	2	5	_		38	ctior	25	0	5	2	3	0	1	0	1	_	_	12
redi	30	1	2	8	5	4	6	2	3	_		31	redic	30	0	0	0	0	0	0	1	0		_	1
4	35	0	0	0	1	1	3	2	1	-	- 2 - 3	8	4	35	0	0	0	0	0	0	0	0			
	>40	0	0	0	0	2	0	0	0	11	0 0	2		>40	0	0	0	0	0	0	0	0	-10	- 18	3 5
		34	0		-	8	0 0		\vdash						5 <u>.</u>	<u> </u>	<u></u>	8	-	-	-	-		-	<u> </u>
	total	34	59	60	55	46	21	8	14			297		total	91	97	63	25	14	4	2	1			297

Fig. 6. Accuracy assessment matrices for categorized interval results from comparison of the four primary component predictions against independent validation points.

4.3 Summation and LANDFIRE comparison

The four primary component predictions (bare ground, herbaceousness, litter, and

shrub) were summed for Landsat and AWiFS cells in range only areas. Landsat

predictions had 9% of the cells summing to exactly 100%, 73% of cells summing

between 95 and 105%, and 93% of cells summing between 90 and 110%. When summed

for the entire state, including Landsat and AWiFS prediction areas, 8% of the cells

summed to exactly 100%, 70% of the cells summed between 95 and 105%, and 92% of the cells summed between 90 and 110% (Fig. 7).



Fig. 7. The statewide summation of the four primary component predictions (bare ground, herbaceousness, litter, and shrub) for Landsat and AWiFS cells in modeled areas. Light tan areas are non-rangeland areas masked from modeling. Overall, 8% of the cells summed to exactly 100%, 70% of the cells summed between 95 and 105%, and 92% of the cells summed between 90 and 110%.

When comparing our independent accuracy assessment plots to LANDFIRE

predictions, we found that our sagebrush components outperformed LANDFIRE

predictions. The shrub component RMSE value was 6.04 versus 12.64 for LANDFIRE,

and the herbaceous component RMSE value was 12.89 versus 14.63 for LANDFIRE

(Table 5).

Table 5. Shrub and herbaceous component and LANDFIRE predictions compared to independent validation plots. Cover predictions for LANDFIRE were reformatted from 10% interval categorical classes into continuous fields for this comparison.

Product	Component	N	R ²	RMSE		
Sagebrush	Shrub (%)	300	0.28	6.04		
LANDFIRE	Shrub (%)	300	0.07	12.64		
Difference			<.021>	<6.60>		
Sagebrush	Herbaceous (%)	300	0.14	12.89		
LANDFIRE	Herbaceous (%)	300	0.07	14.63		
Difference			<0.07>	<1.74>		

5. Discussion

Our results demonstrate the ability of RTs to successfully parameterize all three scales of imagery into nested continuous fields for sagebrush rangelands, and further confirm the multi-spatial scaling concept previously explored (Baccini, et al., 2007; Laliberte, et al., 2007). However, our work took the concept one step further, producing a RT pixel-based prediction at all scales of imagery, including QB, to allow thematic nesting of all product scales. Our research advancements have centered on using optical image and ancillary input data in combination with extensive field data to develop component products that characterize a large area of sagebrush lands while still providing the capacity for local detail and quantitative monitoring.

5.1 Field and QB data

We ultimately field sampled over 32,000 individual $1-m^2$ quadrats across the state of Wyoming for component prediction. Given the substantial component and sensor scale differences, identifying an optimal sampling strategy is challenging (Atkinson and Curran, 1995). However, in our experience field information collected from these 1-m quadrats, and subsequently averaged over 30-m transects, remained generally effective for training the QB 2.4-m predictions. Sample site selection protocols using QB segmentation helped to optimize field collection and provide homogeneous sampling locations for QB classifications. Using QB component predictions as "super plots" for coarser scale imagery provided more abundant training data for RT model parameterization than directly using field plots could have leveraged. However, this field sampling approach was occasionally inadequate for capturing full component ranges at the QB scale, which necessitated periodic micro-plot sampling on smaller heterogeneous QB patches to measure extremes. Future transect design modifications that give additional consideration to capturing more extreme high and low component range measurements would likely improve QB RT models.

Synergizing QB image collection and field sampling (n = 30) was logistically very difficult and we achieved only varied success. Collection differences spanned a range of 1-104 days (mean difference of 39 days, with a standard deviation of 25 days). Larger differences between field sampling and image collection increased the possibility of confounding effects from phenology differences, especially with more dynamic herbaceous, litter, and bare ground components. However, there was no regional cluster pattern observed with QB images within Landsat path/rows of either large or small sampling delays (meaning every Landsat model usually had some of each), which we assumed helped minimize some potential confounding effects. Future exploration of the component accuracy relationship caused by phenological differences between collection times is still needed.

5.2 Model Performance

Representing and understanding overall model performance over such a large area with so many independent models (72 at the Landsat level alone) is a complex undertaking. Only validation results averaged across many models are presented here, with further analysis of localized results beyond the scope of this paper. However, we report model performance using different statistical measures and data comparison scenarios to help present a more complete assessment and to encourage careful interpretation of product accuracy by potential users.

Overall, examination of R^2 values from correlation analysis reveals variable results by component and sensor, with Landsat having the highest mean R^2 for cross validation (possibly due to the more compressed range over QB) and QB by far the highest values from the independent assessment (Table 3). Bare ground was our best performing component prediction across all scales, which is consistent with other rangeland assessments (Booth and Tueller, 2003; Hunt Jr, et al., 2003). Herbaceous component results were modest at the QB scale, but were much poorer at the Landsat and AWiFS scale. One factor in this pattern may be the more compressed ecological range of herbaceousness as the spatial scale changed over QB (see Fig. 5 scatterplot). Poor results are also likely the result of confounding phenological error introduced through the QB prediction training or the impact of combining across year (2006 and 2007) Landsat data for component generation. Secondary shrub components of sagebrush and big sagebrush also had relatively low R² values at the Landsat and AWiFS level, with Wyoming sagebrush and shrub height exhibiting especially poor R² values. However, our big sagebrush results were similar to those reported by Jakubauskas et al. (2001), who used a RT with multitemporal SPOT reflectance data in a Wyoming sagebrush environment in Grand Teton National Park. However, they report higher R² results for bare ground (.66) and shrub height (~.46), which is likely a function of both higher spatial resolution imagery and more localized models compared to our large-area estimates. Similarly, in more localized Landsat model areas classified with this method we experienced R² results for bare ground at .73 and shrub height t.61 (Homer, et al., 2009).

The universally low R^2 values derived from comparison of image NDVI to the independent assessment plots highlight the low photosynthetic signal potentially available for classification in a sagebrush environment (Huang, et al., 2010; Langs, 2004; Sivanpillai and Booth, 2008). Comparison of NDVI results with component R^2 values illustrates the substantial improvement our modeling approach provides over a single model using NDVI alone. It also suggests that discriminating shrub and sagebrush is in part dependent upon other factors than photosynthetic signal, such as canopy shadow – especially for shrub height (Colwell, 1981). The substantial difference between crossvalidation R^2 values and those from the independent assessment should also be noted. Although cross-validation R^2 values are typically optimistic, the larger than expected difference suggests some of our RT models were still not robust enough for the complexity of all unseen pixels, and model parameterization could still be improved.

RMSE is potentially the single most useful metric for gauging our product utility. Mean RMSE across all canopy components (excluding shrub height) averaged 6.32 for QB, 8.66 for Landsat, and 9.09 for AWiFS. Accuracies tended to be higher for components with greater natural ranges in their continuous fields (Fig 4). However, the relatively small reduction in component accuracy from the QB to the Landsat and AWiFS scales is encouraging, given greater demands of extrapolating the models over a much larger spatial extent with greater ecosystem variation and complexity. RMSE values varied substantially not only by sensor but also by location. For example, across individual QB images RMSE values were both remarkably low and disappointingly high. QB site 19, which had simple topography and uniform vegetation, had RMSE values of 2.16% for sagebrush and 6.97% for bare ground, with an average RMSE across canopy components (excluding shrub height) of 3.59%. In contrast, complex topographic and vegetative QB site 30 had the greatest RMSE values of 3.76% for sagebrush and 20.58% for bare ground, with an average RMSE across all canopy components of 10.36%. Examination of the NRMSE values (Table 3) reveals that components with a much broader data range (bare ground, herbaceous, litter, and shrub height) are performing slightly better than components with compressed data ranges (shrub, sagebrush, big sagebrush, and Wyoming sagebrush; Fig 4). NRMSE values suggest that big sagebrush is the poorest performing prediction, further highlighting the challenge of characterizing sagebrush sub-species.

In order to better understand primary component error distribution within each prediction, we categorized values to calculate an error matrix and a linear kappa. Bare ground, shrub, and litter kappa values showed fair agreement (.38, .31, .29 respectively), with the herbaceous kappa value showing only slight agreement at .14 (Table 4). The order of kappa agreement is identical to the order of Landsat R² values for primary components (Table 3). For bare ground, the bulk of the values are distributed between 40 and 80%, with the vast majority of prediction error within 10-20% of the target class, corresponding to the 15.54 RMSE value reported for this component. Off diagonal bare ground values exhibit an under-prediction bias in the matrix. Although the herbaceous values ranged from 10 to 80%, almost all values fell in the10-30% range, creating a substantially compressed predictive data range, which likely contributed to both the lower prediction success and lower kappa value. Herbaceous values display a small overprediction bias in the matrix. Because of their smaller overall data ranges, both shrub and litter were categorized in 5% intervals, with the majority of shrub values ranging between 5 and 20% and litter between 5 and 30%. Both components displayed off diagonal error patterns that would be expected from their RMSE values, with most shrub errors one 5% category away (RMSE 6.01) and litter error typically within two 5% categories (9.34 RMSE). Both components also displayed a slight over-predictive bias in the matrix.

5.3 Other considerations

The general pattern of loss of accuracy as grain size of imagery increases can be partly attributed to the Modifiable Areal Unit Problem (MAUP), (Jelinski and Wu, 1996) where aggregation can cause different variance patterns in the data. In our case, the modeled range of a given variable can become compressed as the spatial size of the pixel increases. Because ecological features such as shrubs have small canopies with wide spacing between individual plants, the dynamic range of cover estimates for 2.4-m pixels can range from 0 to 100%, whereas the dynamic range at 30-m cell size only varies from 0 to ~50%. Additional prediction complications also come from resistance of regression trees to adequately model outliers, further reducing the dynamic range of predicted values. While our approach of weighting training data to influence the RT to better capture the full dynamic range of the predictions helped to overcome some of the outlier issues, the influence of the MAUP and RT biases cannot be entirely overcome as scales change. Component predictions tend to be most accurate in the middle ranges, with lower accuracies at the extremes of measured values from the field.

5.4 Summation Analysis and LANDFIRE Comparison

Our summation analysis of the four primary components revealed 93% of all cells were within ±10% of the desired 100% target. Under-prediction areas are dominant in mountain foothills, which may contain some tree canopy cover, and in the eastern parts of the state, which has a much higher proportion of grass than shrub. Over-prediction also commonly occurs in the grass dominated areas of eastern Wyoming, suggesting less model accuracy as grass dominance increases. Some over-prediction artifacts are also evident in some Landsat scene overlap areas, which were caused by summing unique edge-matching extents for each component. This resulted in some cells containing component predictions from two different path/rows summed into a single value (Fig. 6). However, when considering the potential individual RMSE contribution of each component, the potential for some evaluated pixels to still contain non-range elements missed in our masking, and the number of models required for our large area, 93% is a metric that seemed reasonable to us. Additionally, our shrub and herbaceous component predictions represent significant improvements over the only existing large-area product we have for comparison (LANDFIRE), which further demonstrates component improvement. However, since LANDFIRE is circa 2001 and our products are circa 2006, results should be interpreted with some caution, as some landscape change in sampled areas over this five-year interval is conceivable.

Overall, component prediction accuracy appears to have been limited most by various spatial, spectral, and ancillary data discrimination limitations which varied by sensor and location. In some models this was additionally complicated by the lack of training data robustness over unsampled areas, suggesting that even with our extensive field campaign some RT models would have further benefited from better training. Wider component range sampling within QB areas, more careful spatial distribution of QB images on Landsat path/rows for optimizing landscape representation (Yang, et al., 2003), and better matching of QB image collects and field sampling are all likely areas of future improvement. Given our extensive efforts to already involve multi-seasonal image sources in our existing RT models, future accuracy gains seem unlikely through incorporating additional image seasons; however, limiting cross-year image pooling as we were forced to do would likely reduce some error. Other new optical remote sensing sources with additional new spectral bands may also be helpful. Further accuracy improvement could likely be realized with improved ancillary source data (e.g., higher
resolution Digital Elevation Models) or alternate remote sensing sources such as radar (Huang, et al., 2010), hyperspectral (Mundt, et al., 2006), or lidar (Sankey and Bond, 2011) that provide additional discrimination not available from traditional optical remote sensing.

Our approach of a prediction strategy with multiple spatial scales based on continuous field components is new to sagebrush characterization. We assume this approach offers a more objective way to assemble and re-measure ecosystem variables than traditional land cover mapping. Our underlying motivation for testing this multiscale characterization approach was to design a monitoring framework that can realistically operate over large areas at a cost that is sustainable (Booth and Tueller, 2003). In our case, total potential characterization costs for the four combined primary components at our project economy of scale (in U.S. dollars) are roughly \$2.00 a hectare for QB, \$.025 (2.5 cents) a hectare for Landsat, and \$.01 (one cent) a hectare for AWiFS. We assume costs for repeated measurement will be a fraction of the original characterization cost if update methods target only changing patches (Xian and Homer, 2010), keeping monitoring costs relatively low for coarser scales of imagery.

6. Conclusions

Our approach produced four primary and four secondary continuous field sagebrush components nested at three spatial scales. Methods centered on using a RT classification algorithm to make component predictions from multiple image and ancillary input layers parameterized with direct field data at the QB level, and subsequently with QB predictions as field data for Landsat and AWiFS predictions for all of Wyoming. Primary component accuracies included RMSE values ranging from 4.90 to 10.16 for 2.4-m QuickBird, 6.01 to 15.54 for 30-m Landsat, and 6.97 to 16.14 for 56-m AWiFS. Secondary component accuracies included RMSE values ranging from 4.76 to 7.95 for 2.4-m QuickBird, 5.46 to 11.20 for 30-m Landsat, and 6.11 to 10.18 for 56-m AWiFS. Landsat and AWiFS component products provide enough detail for local application, span large enough areas for ecosystem analysis, and provide a more quantitative framework for future monitoring. Research on component applications analyzing current and historical vegetation change, climate variation, sage grouse habitat distribution, and grazing trends are now in process and will be reported in subsequent papers.

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CHAPTER 3

DETECTING ANNUAL AND SEASONAL CHANGES IN A SAGEBRUSH ECOSYSTEM WITH REMOTE SENSING DERIVED CONTINUOUS FIELDS

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Abstract

Climate change may represent the greatest future risk to the sagebrush ecosystem. Improved ways to quantify and monitor gradual change resulting from climate influences in this ecosystem are vital to its future management. For this research, the change over time of five continuous field cover components including bare ground, herbaceous, litter, sagebrush, and shrub were measured on the ground and by satellite across six seasons and four years. Ground measured litter and herbaceous cover exhibited the highest variation annually and herbaceous cover the highest variation seasonally. Correlation of ground measurements to corresponding remote sensing predictions indicated that annual predictions tracked ground measurements more closely than seasonal ones, and QuickBird predictions tracked ground measurements more closely than Landsat predictions. When annual linear slope values from ground plots and sensor predictions were correlated by component, the direction of ground-measured change was tracked better with QuickBird components than with Landsat components. Component predictions were correlated to annual and seasonal DAYMET precipitation. QuickBird components on average had the best response to precipitation patterns, followed by Landsat components. Overall, these results demonstrate the ability of sagebrush ecosystem components as predicted by regression trees to incrementally measure changing components of a sagebrush ecosystem.

1.0 Introduction

Sagebrush (*Artemisia* spp.) ecosystems constitute the single largest North American semiarid shrub ecosystem (Anderson and Inouye, 2001) and provide vital ecological, hydrological, biological, agricultural, and recreational ecosystem services. (Davies et al., 2007) (Connelly et al., 2004) However, disturbances such as livestock grazing, exotic species invasion, conversion to agriculture, urban expansion, energy development, and other development have historically altered and reduced these ecosystems (Davies et al., 2007) (Leonard et al., 2000) (Crawford et al., 2004) (Davies et al., 2006), with about 50% loss in total spatial extent. (Connelly et al., 2004) (Schroeder et al., 2004) (Hagen et al., 2007) Constant perturbations and changes to these systems are disrupting vital biological services, such as providing habitats for numerous sagebrushobligate species, including the sage-grouse (*Centrocercus* spp.). This has severely impacted sage-grouse populations across their ranges (Connelly et al., 2004) (Garton et al., 2011), leaving populations threatened with extirpation in some habitats where they historically persisted. (Connelly et al., 2004) (Aldridge et al., 2008)

While ecosystem-wide disturbances are having diverse impacts to sagebrush habitats today, climate change may ultimately represent the greatest future risk to this ecosystem. (Neilson et al., 2005) (Bradley, 2010) (Schlaepfer et al., 2012A) (Schlaepfer et al., 2012B) Both warming temperatures and changing precipitation patterns (such as increased winter precipitation falling as rain) will likely favor species other than sagebrush (West and Yorks, 2006) and increase sagebrush disturbance risk from fire, insects, diseases, and invasive species. (Neilson et al., 2005) (McKenzie et al., 2004) Despite the vast area covered by this ecosystem and the numerous disturbance forces operating on the landscape, effective large area monitoring and prediction tools have not been implemented, and widely accepted metrics to quantify and communicate disturbance magnitudes are not well developed. (Washington-Allen et al., 2006) (Washington-Allen et al., 2004) (Booth and Tueller, 2003) (West, 2003) Disturbance monitoring capable of measuring, quantifying, and reporting change in metrics understood by land managers is critical to future successful management of this ecosystem. (Connelly et al., 2004) (Aldridge et al., 2008) (Washington-Allen et al., 2004) (Homer et al., 2012) (Knick et al., 2003)

Optical remote sensing is still the most likely data source and tool for large area monitoring of disturbance within the sagebrush ecosystem, supporting a framework that can offer relatively efficient and accurate analysis of change across a range of spatial and temporal scales. (Homer et al., 2012) (Xian et al., 2012B) (Ramsey et al., 2004) Sagebrush ecosystems represent a challenging remote sensing environment because these semiarid shrublands have sparse and similar vegetal cover with high proportions of bare ground and a variety of soil reflectance properties. (Okin and Roberts, 2004) (Graetz and Pech, 1988) Despite these challenges, an optical remote sensing signal capable of characterization exists for semiarid shrublands, and monitoring is feasible. (Graetz and Pech, 1988) (Homer et al., 2009) (Anderson et al., 1993) (Tueller, 1989) (Graetz et al., 1983) (Musick, 1983) (Robinove et al., 1981) Studies within the sagebrush ecosystem have demonstrated the ability for remote sensing to characterize more abrupt types of disturbance from fire (Norton et al., 2009) (Sankey et al., 2008) and human development (Sivanpillai et al., 2009) (Walston et al., 2009) and gradual types of disturbance such as grazing (Bork et al., 1999) and climate change. (Xian et al., 2012B)

A comprehensive understanding of the relationship between remote sensing change and gradual changes in sagebrush ecosystem components is still lacking; only a few studies have begun to explore that relationship. (Ramsey et al., 2004) (Walston et al., 2009) (Baghzouz et al., 2010) (Vogelmann et al., 2012) (Xian et al., 2012A) Further, even beyond the sagebrush ecosystem to semiarid systems in general, remote sensing change studies have historically targeted the development of indices such as the normalized difference vegetation index (NDVI) or other similar approaches to understand change. (Brinkmann et al., 2011) (Todd et al., 1998) (Duncan et al., 1993) These indices can be difficult to interpret and translate to on-the-ground understanding. (Gottschalk et al., 2005) (Coppin et al., 2004) (Hunt, Jr. et al., 2003)

Metrics that characterize changes that managers readily use in the field for realtime decisions, such as fractional vegetation predictions, (Homer et al., 2012) would more likely ensure application of such products for daily management decisions and applications. Recent research has sought to reconcile this need, with approaches centered on using a single year of training data to parameterize a base characterization layer, which is then projected through several time periods using change vector analysis to identify what change is occurring. This approach assumes change areas identified in the change vector process can be labeled using values from the base characterization layer. (Vogelmann et al., 2012) (Xian et al., 2012A) However, no research has tested this assumption by gathering repeated ground measurements over many time steps (seasons or years) to fully evaluate the ability of the change vector approach to detect fine scale change within sagebrush ecosystems.

Technological advances have also resulted in the development of higher spatial resolution sensors offering new potential for monitoring in sagebrush ecosystems at resolutions finer than Landsat. (Booth and Tueller, 2003) (Homer et al., 2012) (Mirik et al., 2005) (Witztum and Stow, 2004) (Jakubauskas et al., 2001) New spectral bands at finer spatial resolution can increase our ability to detect smaller changes and improve monitoring applications. Increased sensor resolution may allow for changes to be detected at more local scales, enhancing interpretation and understanding. Also, because ground measurement approaches are often prohibitively expensive, high resolution sensors offer the potential to extrapolate ground measurement across larger landscape models and also provide an operational surrogate for ground plot re-measurement. However, studies that explore the capabilities of higher resolution sensors to complement and support component predictions derived at moderate spatial scales for change monitoring have not been completed.

Downscaling of climate information such as precipitation also continues to evolve to better support more localized analysis. The release of new data with longer temporal records and at finer spatial scales provides new opportunities for defining the relationship between climate change and sagebrush ecosystem change. Specifically, the new release of DAYMET Daily Gridded Surface Climate Data, (Thornton et al., 1997) providing daily precipitation data at a 1-km spatial resolution, provides a new opportunity to explore potential finer scale links of climate change to any observed ecosystem change.

We attempt to address these research gaps by capitalizing on advancements in high-resolution remote sensing data availability, remote sensing component prediction and change detection, and new availability of higher spatial resolution precipitation. With the goal to explore if component change and precipitation impacts can be detected across multiple scales of remote sensing in a sagebrush ecosystem. Ongoing ground and satellite monitoring of several focus areas in Wyoming provide the opportunity to explore change patterns from a variety of drivers. For this evaluation, we focus on one particular monitoring site, labeled "1." Site 1 has had no observed potential change drivers during field visits or in any satellite images other than climate influences during the timeframe of this study, offering a good opportunity to examine ecosystem change driven only by variation in climatic conditions. We tracked component change in this sagebrush ecosystem across four years and six seasons (during the first two years) using multi-year satellite imagery and ground-based vegetation sampling. The spatial distribution and temporal change for fractional cover components of bare ground, herbaceous, litter, shrub, and sagebrush was quantified between 2008 and 2011. Our specific study objectives were to (1) determine the relationship between changing spatial and temporal extents of fractional component change as measured from three scales, including ground measurement, QuickBird (QB) 2.4-m satellite acquisitions, and Landsat 5 (LS) 30-m satellite acquisitions; (2) quantify, compare, and contrast observed changes of remote sensing sagebrush ecosystem components across years and seasons with ground measurements; (3) test if remote sensing components trained on a single base year (2008), and subsequently extended through time using change vector analysis (20092011), are sensitive enough to capture subtle ground-measured change over time; and (4) use DAYMET precipitation data to evaluate if precipitation changes correlate with annual and seasonal component change identified from ground-measurement, QB predictions, and LS predictions.

2.0 Data and Methods

2.1 Overview

Our approach examined two years of seasonal sagebrush ecosystem change nested within four years of annual sagebrush ecosystem change using data collected from ground measurements and remote sensing data from QB and LS. We measured proportional amounts of each of five sagebrush ecosystem fractional cover components (hereafter simply called components) including cover of bare ground, herbaceous, litter, sagebrush (all species), and shrub (all shrubs combined) as continuous fields in 1% intervals using both ground plots and satellite predictions. Using 2008 ground measurements, we produced QB and LS satellite data component predictions for the study area. The percent cover of each component was then both annually and seasonally updated only in areas that had spectrally changed from the 2008 base year or season. These updates were completed with regression trees using unchanged 2008 base areas as training sources. We collected field data in other years and seasons for evaluation of these predictions. Correlation analysis was then conducted to explore relationships between various ground, satellite, and precipitation measurements. We explain each methodological step by section below.

2.2 Study Area

The study was conducted in southwestern Wyoming, United States. One 64-km² area (Site 1) was selected as a focus area for intensive ground measurement coupled with QB and LS measurements (Figure 1). This site represented one of 30 sites used for initial 2006 Wyoming sagebrush characterization. (Homer et al., 2012) Site 1 is located approximately 22 km southeast of Farson, Wyoming. It contains a range of topography with elevations from 2026 to 2327 m, and slopes up to 31 degrees. It has predominately sandy soils and contains part of the Farson sand dunes in the northeast corner. Vegetation is dominated by sagebrush shrubland, especially in the upland areas, with salt desert shrub species dominating in the lowland and sandy areas. Herbaceous areas range from typical grasses and forbs interspersed among shrubs to sub-irrigated meadows where a high sub-surface water table in the sand dune areas creates higher than normal biomass productivity for these selected areas. This site is public land administered by the Bureau of Land Management and is typically grazed by cattle most of the summer. During our study we observed no substantial differences in the amount or duration of grazing from year to year.



Figure 1. Location and spatial extent of the study area Site 1 used for monitoring sagebrush component change from 2008 to 2011 in southwestern Wyoming.

2.3 Baseline Data Collection

Plot Selection and Measurement

We segmented the QB imagery into spectrally similar polygon patches to identify sites for potential ground sampling. We also classified the image into 30 unsupervised clusters. Segmented polygons were then intersected with the 30 clusters to identify the majority cluster class in each polygon, and 66 polygons representing the full range of spectral variability across the QB image were then selected. (Homer et al., 2012) Ground measurements were conducted using ocular measurements at 7 1-m² quadrats along each of two 30-m transects within each polygon plot. (Homer et al., 2012) (Homer et al., 2009)

To ensure re-measurement was spatially over the same quadrat areas, we permanently staked the beginning and ending of each transect. Cover was estimated from an overhead perspective (satellite), with the total cover of all vegetation and soil components summing to 100%. The shrub component represented all woody shrub species; the sagebrush component is a subset of the shrub component and represented only sagebrush shrub species (*Artemisia spp.*); the herbaceous component represented all grasses (live and residual standing) and forbs; litter is the combined cover of dead standing woody vegetation and detached plant and animal organic matter; and the bare ground component represented any exposed soil or rocks. All individual quadrat cover estimates were made in 5% increments. Ground measurements were conducted annually on the same approximate dates, with QB image acquisition attempted as near these dates as possible. Plot measurements for 2008-2011 were conducted by the same two individuals over the same plots every year, except in 2011 when the alternate observer sampled all plots.

Image Collection and Pre-processing

QB images covering the study area were targeted seasonally (spring, summer and fall) for 2008 and 2009, and annually during each of the summers of 2008 through 2011. Four-band multispectral images (visible blue, green, red, and near infrared) were collected at 2.4-m resolution with a desired target of below 20 degrees off-nadir view angle. Imagery was processed by Digital Globe to UTM using a 2x2 bilinear re-sampling kernel. We used the ERDAS 10 AutoSync tool to accomplish QB orthorectification using 1-m National Agricultural Imagery Program (NAIP) imagery as the base. The AutoSync tool uses an automatic point matching algorithm to generate hundreds of tie points

between the reference image and the subject image to complete the geometric correction. This functionality is sensor specific and enhanced with the use of a Digital Elevation Model (DEM). Subsequent years of QB imagery were registered to the orthorectified 2008 image base to ensure spatial consistency using the same process as described above. QB images were converted to at-sensor reflectance using the following equation:

$$\rho_{\lambda} = \frac{L_{\lambda} \times d^{2} \times \pi}{Esun_{\lambda} \times \cos(\theta_{s})}$$

where

 $\rho_{\lambda} = \text{Planetary TOA reflectance [unitless]}$ $\pi = \text{Mathematical constant equal to ~3.14159 [unitless]}$ $L_{\lambda} = \text{Spectral radiance at the sensor's aperture [W/(m^2 \text{ sr } \mu \text{m})]}$ d = Earth-Sun distance [astronomical units] $Esun_{\lambda} = \text{Mean exoatmospheric solar irradiance [W/(m^2 \, \mu \text{m})]}$ $\theta_s = \text{Solar zenith angle [degrees]}$

This is similar to the approach used for converting the LS imagery to at-sensor reflectance. (Chander et al., 2009A) (Chander et al., 2009B) Results were then converted to 8 bit files using a scaling factor of 400 to remain consistent with the way the LS was processed.

Multi-season and multi-year LS imagery from 2008-2011 was acquired for path 37 row 31 and processed using the automated Level 1 Product Generation System (LPGS). Through this process the scenes were converted to at-sensor reflectance, projected to Albers Equal Area, and terrain corrected. (Xian et al., 2012A) (Chander et al., 2009B) (Xian and Homer, 2010) (Xian et al., 2009) The positional accuracy of all LS

and QB images was carefully controlled to ensure direct comparisons of multiple dates and image platforms were spatially accurate.

Component Predictions

The 2008 base spatial distributions of five components of sagebrush habitat including cover of bare ground, herbaceous, litter, shrub, and sagebrush were estimated at 1% intervals for both QB and LS using regression tree models. For QB, 120 ground transects, with four additional mini plots centered over very high component value areas, were used for regression tree training. Vegetation characteristics were sampled at seven $1-m^2$ quadrats along 30-m transects in sample polygons. The mean value for each of the variables of interest was calculated across all 7 1-m quadrats within a transect. These values were assigned to all pixels occurring within the sampling area for each transect. The five component predictions within the QB image were developed independently from multispectral QB and ancillary data using the regression tree (RT) algorithm Cubist (Anderson and Inouye, 2001) (Quinlan, 1993) following a protocol developed in an earlier study. (Homer et al., 2012) For LS, QB predictions from three sites (including Site 1) across the LS TM scene were combined to build training data for the LS modeling. These additional sites provided variation in land cover types resulting in comprehensive training across the entire TM scene and replicated a typical full TM scene component modeling scenario. (Homer et al., 2012) We purposely developed the LS prediction with the full TM scene perspective to ensure that the predictions at Site 1 represent a typical landscape level application. We refined the training by dividing the data for each of the five component predictions into roughly three equal bins based on the mean and root

mean square error (RMSE). The middle bin was thinned more relative to the other bins to ensure that higher and lower component values carried appropriate weighting in the model development and reduced overall bias. LS predictions were modeled using one leaf-on image from each year for annual predictions and one seasonal image from each season of each year for seasonal predictions, coupled with DEM ancillary data.

Image Normalization and Change Identification

The process of normalizing many image dates to ensure consistent comparison is important for initiating trend analysis. Once images are normalized, potential change areas need to be identified and the magnitude and type of change labeled. We accomplished this process by following several major processing steps. For QB, all cloud and cloud shadow areas in the scenes were masked and excluded to ensure these areas did not incorrectly influence the normalization outcome. Next, NDVI was calculated for each image, and a difference layer was calculated, to compare NDVI magnitude differences between the reference scene (from 2008) and the subject scene. Experimental trials of different NDVI thresholds revealed that a threshold of ± 5 NDVI values was appropriate for excluding outlier pixels from influencing the normalization process. This process of outlier pixel exclusion ensured normalization was developed from only the most invariant pixels. Finally, a linear regression algorithm was developed from the invariant pixels and used to relate each pixel of the subject image to the reference image (2008 image) band by band. (Xian et al., 2012A) For LS, a similar approach was followed. First, all cloud, cloud shadow, and snow and ice areas were excluded from analysis. Then, a normalization procedure using a linear regression algorithm to relate each pixel of the

subject image to the reference image (2008 leaf-on) band by band was conducted. (Xian et al., 2012A)

Once image normalization was completed, images across years and seasons were compared for identification of change areas using a change vector process. For QB, change pixels were determined using a standard deviation from the mean value. Pixels outside one standard deviation (SD) were considered to be potential change areas. LS change pixels were determined using thresholds specific to general land cover classes spatially identified from the 2006 National Land Cover Database. (Xian et al., 2012A) Change areas identified with the threshold approach tended to be too conservative to capture all change relative to field measurements, and an additional independent approach was necessary to further capture potential change areas with more subtle change. This additional approach used NDVI differencing between the master scene (2008) and the subject year or season to confirm change pixels. Research trials showed that pixels outside of \pm 5 NDVI values for QB and outside of \pm 3 values for LS needed to be retained as change pixels (the greater sensitivity of QB to image noise artifacts necessitated a higher threshold than LS to maintain comparability across sensors). The final potential change mask was created combining (union) both the change vector process and the NDVI differencing results. All cloud and cloud shadow areas were treated as no change areas and removed from the change mask image.

Labeling annual and seasonal subsequent change areas with the new component values was accomplished for both QB and LS by using a RT modeling approach and input data layers similar to that used to predict the 2008 baseline distributions. Training

data were gathered from the 2008 unchanged baseline component values after first excluding potential change pixels by using the change masks described above. A random sample of 10,000 points for QB and 25,000 points for LS were selected from candidate pixels for each component. Predictions quantifying the spatial distribution and per-pixel proportion of five components as a continuous variable were then calculated using regression models for all change pixels in each at sensor reflectance QB and LS image. Baseline predictions for spectrally unchanged pixels were not modeled and were left as original predictions from the base year. Using the change mask created from the change vector process, each of the change pixel prediction values was then applied over the base prediction. The no-change pixels retained the prediction value from the base prediction, and only the change pixel areas were updated for each new imagery date. (Xian et al., 2012A)

2.4 Data Analysis and Evaluation

Data summation and analysis protocols – plot level polygon data

Both QB and LS predictions were evaluated by comparison to corresponding ground plot measurements within plot polygons and analyzed by component and data source. Component values measured at ground plots were compiled into a single mean transect value (7 individual frames on a 30-m transect) for comparison to QB, and by plot (two transects, 14 individual frames) for comparison to LS. Similarly, for QB and LS predictions, all pixel values within each ground plot polygon or transect boundary were averaged to represent one component value for each transect/plot (referred to simply as "plot" hereafter). For consistency, the exact same plots were analyzed across all years and seasons. If clouds or other image issues precluded a plot from inclusion from one year or season, it was eliminated from analysis from all dates. This ensured fair comparisons between sensors and components. For each annual and seasonal plot the standard deviation (SD) of the individual frame measurements was calculated. For each annual plot, a slope value from a linear regression was calculated for change over time. In order to facilitate direct comparison among components and data sources, the coefficient of variation (COV) (Mean/SD * 100) was also calculated for each plot.

To determine whether significant change had occurred on ground-measured annual and seasonal plots, a one-way analysis of variance (ANOVA) was performed. This calculation uses the standard deviation from the individual transect frame measurements for each plot to determine whether there are any significant differences between the means of plot measurements across time. All ANOVA significance levels are reported at alpha = 0.1. To determine if a significant direction of change occurred on annual plots, the linear slope was calculated and significance tested at the 0.1 level.

Several combinations of Pearson's correlation were used to compare ground plot measurements to QB and LS predictions. First, in order to test the overall similarity of the component predictions to ground measurements, a correlation analysis comparing plot level mean component values for each of the data sources was completed. Second, correlation was used to test the strength of the relationship between ground measured significant ANOVA plots and significant slope plots to component predictions. Finally, correlation of slope values from both ground measurements and component predictions was used to test the ability of components to track the direction of change over time.

Data summation and analysis protocols – by total proportional area

To test component prediction relationships beyond plot level polygons, ground measurements, QB and LS predictions were also compiled to assess the total area of change of components across the full study area. For ground measured polygons within the Site 1 study area, the total area covered by all polygons was calculated; subsequently, the proportion of that total area covered by each component by year and season was also calculated. For QB and LS, the full study extent of Site 1 predictions were used to calculate the areal proportion of each component of each cell into a total area summary value (e.g., a 50% bare ground prediction in a 30-m LS cell means 50% of the area of that cell is counted as bare ground, or 450 m²). The mean proportional amounts of total area by year and season were calculated for each data source. We calculated the mean epoch to epoch percent change by dividing the percent change of epoch (season or year) by the total number of epochs, and also calculated the mean relative error between component predictions and ground measurement. Pearson's correlation analysis was used to compare proportional component measurements among data sources.

Comparison to precipitation, by source and component

DAYMET daily gridded surface climate data providing daily precipitation data at a 1-km spatial resolution was downloaded for Site 1 for 2008-2011 (Thornton et al.,1997). Daily data were then combined into mean seasonal precipitation amounts by one month and two month intervals for seasonal analysis, and by calendar year and water year (September – October) for annual analysis. Mean monthly and annual DAYMET precipitation values for all cells in Site 1 were then pooled into a single mean value representing the entire Site 1 study area. Corresponding mean monthly and annual total area percent component values from ground measurements and QB and LS predictions for Site 1 were then correlated with precipitation data using Pearson's correlation.

3.0 Results

3.1 Overview

We measured five sagebrush ecosystem fractional cover components including bare ground, herbaceous, litter, sagebrush, and shrub on the ground and from satellites over 6 seasons and 4 years. Comparison analysis of component change patterns among data sources was conducted at both the single plot level and proportionally across the entire study area. Study area proportional seasonal and annual changes were also correlated to annual and seasonal precipitation measurements. Specific results are listed by section below.

3.2 Plot level ground and satellite measurements

A total of 66 ground plots (132 transects) were sampled during the summers of 2008 through 2011 across Site 1. Only plot results from 2008 were used to develop RT predictions for all five components across one 2.4-m QB 64-km² image extent (Site 1) and corresponding LS extent, all other years and seasons were developed using change

vector analysis (Figure 2). The RMSE average for the 2008 base estimate for all five components over Site 1 was 4.68% for QB and 6.83% for LS (Homer et al., 2012).



Figure 2. Site 1 QB (2.4 m) on the left and LS (30 m) 2008 base component predictions on the right. Masked cloud areas in the LS predictions are shown in gray. Note the total range of each component prediction.

Image collection dates deviated an average of 16 days from ground collection for QB and 9 days from ground collection for LS (Table 1). After removing plots affected by clouds on either QB or LS imagery, 52 plots (104 transects) remained for analyses.

 \bar{x} (days) Source SE Spring 2008 Summer 2008 Fall 2008 Spring 2009 Summer 2009 Fall 2009 Summer 2010 Summer 2011 Collection from Field July Ground June July Sept June Sept July July 17 22 22 13 22 22 14 16 QB July July 16 4.5 Oct June Sept Aug Aug -----11 17 3 14 14 12 21 LS 9 3.9 July Sept July June Sept June Aug Aug 20 22 24 23 10 27 13 14

Table 1. Ground measurement dates, with corresponding Landsat and QuickBird image collection dates.

Of the five components, litter exhibited the highest COV for annual groundmeasured change at 18.4%, with herbaceous second at 18.1%, then shrub at 17.2%, sagebrush at 9.9%, and bare ground the lowest at 8.3% (Table 2, Figure 3). Litter had the largest number of plots qualifying as significantly changed from the ANOVA analysis at 15, with herbaceous second at 13, bare ground third at 7, and shrub and sagebrush with one each (Table 2). Only 7 annual plots overall showed significant plot change and significant slope change, two each in bare ground and litter, and one in each of the remaining three components.



Figure 3. Visual example of bare ground component change in the northeastern part of Site 1 from 2008 through 2011 in southwestern Wyoming. QB bands 4, 3, & 2 are displayed as RGB on the left, and the corresponding bare ground component predictions are on the right.

Components	Plots (N)	2008 (mean)	2009 (mean)	2010 (mean)	2011 (mean)	SD (mean)	Coefficient of Variation (mean)	Linear Slope	N with Sig. ANOVA (.10)	N with Sig. Slope (.10)
Bare Ground	52	57	54	56	55	2.88	8.3	1.36	7	2
Herbaceous	52	16	16	15	14	2.42	18.1	1.31	13	1
Litter	52	16	17	16	16	1.94	18.4	0.79	15	2
Shrub	52	11	12	12	13	1.45	17.2	0.76	1	1
Sagebrush	52	6	7	7	8	0.99	9.9	0.53	1	1

Table 2. Mean ground-measured annual change (% of 100) across 52 plots, by component.

For seasonal change, herbaceous exhibited the highest COV for ground measured change at 23.8%, with litter second at 21.4%, then sagebrush at 19.4%, shrub at 18.9%, and bare ground the lowest at 8.7% (Table 3). Litter and herbaceous had the largest number of plots with significant ANOVA-measured change at 23 each, with bare ground next at 11, then shrub with 2, and sagebrush with one (Table 3).

3.3 Plot level data correlation relationships

Each set of values from both annual and seasonal individual ground plots and transects were correlated with the corresponding satellite component measurements to test the ability of the component predictions to replicate ground measurements. Overall, annual predictions were more highly correlated than seasonal predictions, and QB had higher correlation values than LS (Table 4). QB displayed a mean correlation value across all components of 0.85 for annual and 0.82 for seasonal. LS had a mean correlation value across all components of 0.77 for annual and 0.73 for seasonal. For components, bare ground had the highest mean correlation across sensors at 0.91, with shrub exhibiting the lowest correlation at 0.69 (Table 4).

Component	Plot N	June 2008 (mean)	July 2008 (mean)	Sept 2008 (mean)	June 2009 (mean)	July 2009 (mean)	Sept2009 (mean)	SD (mean)	Coefficient of Variation (mean)	N with Sig. ANOVA (.10)
Bare Ground	52	59	57	57	56	54	56	3.42	8.7	11
Herbaceous	52	15	16	14	15	16	12	3.04	23.8	23
Litter	52	15	16	17	16	17	19	2.80	21.4	23
Shrub	52	11	11	11	12	12	12	1.67	18.9	2
Sagebrush	52	7	6	6	7	7	7	1.02	19.4	1

Table 3. Mean ground-measured seasonal change (% of 100) across 52 plots, by component.

Table 4. Remote sensing prediction correlations to annual and seasonal ground measurements over plot areas, by component. (All correlations were significant at the .01 level.)

			ANN	UAL	SEASONAL		
Component		QB	LS	QB	LS		
	QB (transects)	LS(plots)	(R)	(R)	(R)	(R)	IVIEAIN
Bare Ground	104	52	.94	.92	.90	.88	.91
Herbaceous	104	52	.81	.73	.81	.71	.77
Litter	104	52	.93	.87	.87	.80	.87
Shrub	104	52	.77	.63	.75	.59	.69
Sagebrush	104	52	.78	.71	.77	.69	.74
MEAN			.85	.77	.82	.73	

The linear annual slope value was calculated across annual measurements for each plot, QB and LS prediction. These slope values were then correlated to test the ability of component predictions to replicate the trend of ground measured slope change. QB had relatively high correlation values for individual components, and most correlations were significant (Table 5). In contrast, LS had low correlation values for individual components, with significant correlation values only in the bare ground component. When slope values from all plots and transects were pooled across all components (N = 520), QB had a correlation of 0.37 and LS a correlation of .010. When a subset of slope values from only significant ground measured ANOVA plots were pooled (Table 2) (N = 40), QB had a correlation of 0.74 and LS remained at 0.10. However, correlation of slope values from ground measured plots with a subset of both significant ANOVA and slope results (N = 14) yielded a correlation of 0.77 for QB and a correlation of 0.64 for LS (Table 5).

3.4 Total area comparison

The total proportional area covered by each component from each source (ground and satellite) was calculated for each season and year across all of Site 1, with the proportion of change between seasons and years also calculated. For annual predictions, bare ground exhibited the highest mean annual change at 1.3%, shrub the next highest at 0.8%, then herbaceous at 0.6%, litter at 0.5%, and sagebrush the lowest at 0.3% (Table 6). Shrub had the highest mean annual relative error, and litter had the lowest. When compiled by data source, ground measurement showed the highest overall mean change across all components at 1.02%, with LS second at 0.56%, and QB the lowest at 0.52%.

Table 5. Annual component correlations of individual linear slope value calculated for plot measurements, correlated with the linear slope value calculated for corresponding LS and QB predictions. Correlation results reveal the ability of the sensor component predictions to replicate the direction of slope change as measured on the ground.

	QuickB	ird	Landsat		
Component Stratification (ANOVA and Slope Significance from	N (Transect)	R	N (Plot)	R	
field measurements)	101	20*	50	22*	
Bare Ground – all plots	104	.28*	52	.23*	
significant @ .1	9	./8*	/	./3*	
Bare Ground – only plots Slope	3	.92	2	+	
significant @ .1	101	70*	50	00	
Herbaceous – all plots	104	.70*	52	06	
Herbaceous – only plots ANOVA significant @ .1	15	./8*	13	.10	
Herbaceous – only plots Slope significant @ .1	8	.86*	1	+	
Litter – all plots	104	.61*	52	.05	
Litter – only plots ANOVA significant @ .1	13	.78*	15	.23	
Litter – only plots Slope significant @ .1	1	+	2	+	
Shrub – all plots	104	46*	52	.13	
Shrub – only plots ANOVA significant @ .1	3	99*	1	+	
Shrub – only plots Slope significant @ .1	2	+	1	+	
Sagebrush – all plots	104	55*	52	07	
Sagebrush – only plots ANOVA significant @ .1	0	+	1	+	
Sagebrush – only plots Slope significant @ .1	0	+	1	+	
ALL COMPONENTS, All Plots	520	.37*	260	.10	
ALL COMPONENTS, Only Significant ANOVA Plots Combined	40	.74*	37	.10	
ALL COMPONENTS, Only Significant Slope Plots Combined	14	.77*	7	.64	

+ Inadequate sample size

* Correlation significant at 0.1

Ground mean annual change values showed the most variation between components, with

QB showing the least. Overall, QB had higher relative errors then LS (Table 6).

Table 6. Comparison of the percent proportions of total area covered by each component for every year. For ground plots, the total area is calculated from pooling all plot polygons; for QB and LS, the total area is calculated from full study area predictions.

Component	2008	2009	2010	2011	Mean Annual Change (%)	Mean Annual Relative Error (%)
Bare Ground (%)						
Field	59.5	57.1	59.1	57.8	1.9%	
QuickBird	59.7	59.1	59.9	60.6	0.7%	2.5%
LS	60.3	61.4	60.8	58.8	1.2%	3.4%
Mean					1.3%	
Herbaceous (%)						
Field	15.7	15.9	13.5	13.3	0.9%	
QB	12.9	13.3	12.8	12.7	0.3%	10.9%
LS	13.2	12.5	12.9	13.7	0.6%	9.6%
Mean					0.6%	
Litter (%)						
Field	15.4	16.1	14.8	15.5	0.9%	
QB	15.3	15.7	15.6	15.2	0.3%	0.1%
LS	15.4	15.2	15.4	16.2	0.4%	0.7%
Mean					0.5%	
Shrub (%)						
Field	10.2	11.9	12	12.7	0.8%	
QB	9.6	10.4	9.1	10.2	1.1%	15.6%
LS	10.1	9.8	10.0	10.8	0.4%	12.4%
Mean					0.8%	
Sagebrush (%)						
Field	5.8	7.1	7.3	7.6	0.6%	
QB	5.4	6.1	6.1	6.0	0.2%	14.7%
LS	6.2	6.2	6.3	6.8	0.2%	7.4%
Mean					0.3%	

For seasonal measurements, the mean total proportional seasonal change across 6 seasons for ground and LS and 5 seasons for QB was calculated. Bare ground exhibited the highest mean seasonal change at 2.0%, herbaceous next at 1.2%, litter at 0.8%, shrub at 0.7%, and sagebrush the lowest at 0.5% (Table 7). Herbaceous had the highest mean annual relative error, and bare ground had the lowest. When compiled by data source, in contrast to annual measurements, LS showed the highest overall mean seasonal change across all components at 1.90%, with ground second at 0.7%, and QB the lowest at 0.52%. The seasonal change values showed the most variation between components from LS, with QB showing the least. Overall, LS had higher relative errors then QB (Table 7).

3.5 Total area correlation to precipitation data

DAYMET annual precipitation at Site 1 varied from a low of 219 mm in 2009 to a high of 297 mm in 2011 (Figure 4). With seasonal scenarios varying from a low of 2 mm in August/September 2008 to a high of 67 mm in June 2008 (Figure 5). Correlation of mean monthly and annual DAYMET precipitation values to the corresponding mean monthly and annual total area component calculations is presented in Table 8. Of the 60 scenarios tested, only 9 were significant at the 0.1 level. When correlations were averaged across components, herbaceous had the highest mean correlation across all seasonal and annual scenarios at 0.67, and shrub the lowest at 0.47. When correlations were averaged by data source, the highest mean correlation at 0.29 (Table 8). The highest significant individual correlation scenario was ground plot herbaceous against calendar vear precipitation at -0.99. Table 7. Comparison of the percent proportions of total area covered by each component for every season. For ground plots, the total area is calculated from pooling all plot polygons; for QB and LS, the total area is calculated from full study area predictions.

Component	June 2008	July 2008	Sept 2008	June 2009	July 2009	Sept 2009	Mean Seasonal	Mean Annual
							Change (%)	Relative Error (%)
Bare Ground								
Field	61.4	59.9	60.1	58.5	57.8	58.8	0.9%	
QB	*	59.9	60.7	59.8	59.5	62.4	1.2%	2.4%
LS	57.0	60.6	60.7	55.7	61.8	65.6	3.8%	1.4%
Mean							2.0%	
Herbaceous								
Field	13.4	14.0	13.3	14.0	14.3	12.0	1.0%	
QB	*	12.8	11.9	12.6	13.0	11.7	0.8%	8.4%
LS	13.7	12.8	12.3	14.4	12.2	10.4	1.7%	6.7%
Mean							1.2%	
Litter								
Field	13.8	15.5	15.6	15.3	16.2	17.8	0.7%	
QB	*	15.6	15.7	15.8	15.7	14.9	0.3%	2.9%
LS	16.8	15.4	15.8	17.8	15.3	14.2	1.5%	2.0%
Mean							0.8%	
Shrub								
Field	10.0	09.6	10.1	11.0	11.1	10.8	0.5%	
QB	*	10.4	10.3	10.4	10.4	10.0	0.2%	1.6%
LS	11.9	10.1	10.4	12.5	09.9	09.1	1.5%	2.5%
Mean							0.7%	
Sagebrush								
Field	06.5	05.6	05.7	06.9	06.8	06.6	0.4%	
QB	*	06.1	06.3	06.2	06.1	06.1	0.1%	1.6
LS	07.8	06.3	06.7	08.2	06.3	06.4	1.0%	10.2
Mean							0.5%	

* No data collected



Figure 4. Annual precipitation measurements for Site 1, compiled by calendar year and water year, in millimeters.



Figure 5. Seasonal precipitation measurements for Site 1 compiled both monthly and bimonthly, in millimeters.
Table 8. Correlation (R) of annual and seasonal precipitation measurements over Site 1, to corresponding annual and seasonal component change from ground plots and sensor predictions.

	Ground Plots, Site 1				QB, Site 1				LS, Site 1				
	Seasonal		Annual		Seasonal		Annual		Seasonal		Annual		
Component	Month of ground sample	Bi- month of ground sample	Calendar year	Water year (Oct- Sep)	Month of ground sample	Bi- month of ground sample	Calendar year	Water year (Oct- Sep)	Month of ground sample	Bi- month of ground sample	Calendar year	Water year (Oct- Sep)	MEAN
Bare Ground													
	04	14	.26	46	62	-75*	.87	.77	38	38	60	86	.51
Herbaceous	.47	.74*	99*	56	.82*	.95*	90*	47	.37	.47	.62	.72	.67
Litter	49	39	76	.17	.35	.42	53	70	.28	.26	.65	.95*	.50
Shrub	.21	.01	.55	.66	.49	.60	.46	.52	.34	.26	.66	.93*	.47
Sagebrush	.54	.27	.55	.60	60	65	.38	.33	.28	.09	.72	.95*	.50
Mean	.35	.31	.62	.49	.57	.67	.63	.56	.33	.29	.65	.88	

* Correlation significant at 0.1

4.0 Discussion

Our results demonstrate reasonable ability of sagebrush ecosystem components as predicted by regression trees to incrementally measure changing components of a sagebrush ecosystem. Specifically, we demonstrate the ability of regression tree component predictions to track ground-measured change over time using ground data from one year and change vector analysis for subsequent years. We demonstrate the ability of high spatial resolution satellite imagery to serve as a potential surrogate for repeated ground measurement. Finally, we demonstrate the ability of component predictions to potentially monitor vegetation change related to precipitation variation over time. Specific discussion topics are covered below.

4.1 Ground-Measured Component Change

Ground measurements reveal a subtle changing landscape both seasonally and annually (Tables 2 and 3). This is to be expected, given that we could observe no other major change agent operating in this area, other than climate. (Xian et al., 2012B) (Xian et al., 2012A) However, it is encouraging that we were able to observe and detect this subtle change from both a ground and remote sensing perspective. We went to great lengths to ensure ground measurements were consistent by using staked plots, re-visiting plots at the same time of year and season, and having the same observer repeat measurements. The only exception was from 2011, when 35 plots were measured by the alternate observer; however, a quality check of these data revealed the measurement pattern to be consistent with previous measurements both observers had completed.

Component change varied by season and year, with seasonal measurements in every component consistently showing a higher COV than annual measurements (Figure 6). This follows an expected ecosystem pattern, with seasonal plant response potentially more dynamic than annual response. (Bates et al., 2006) (West 1999) For individual components, litter and herbaceous exhibited the highest COV from annual measurements, and herbaceous the highest for seasonal measurements. These results are logical due to the ephemeral nature of these components with changing precipitation. (Bates et al., 2006) The shrub and sagebrush components exhibited relatively moderate COVs in both seasonal and annual measurements, with sagebrush having a substantially lower annual COV than shrub (Figure 6). Sagebrush species contain some ephemeral leaves, which are dropped later in the growing season, (McArthur and Welch, 1982) (Caldwell, 1979) and we suspect this change is detected on the seasonal plots from spring measurement, but not on summer measured annual plots. Alternatively, the shrub component contains many additional shrub species besides sagebrush that exhibit sustained growth through the entire season, resulting in similar change patterns for both annual and seasonal measurements. Because of the relatively high SD exhibited by bare ground, we did not anticipate that it would have the lowest COV of any component in both seasonal and annual measurements (Table 2, Table 3). However, high proportions of bare ground on many of our plots resulted in a large dynamic range for this measurement which was factored out by the COV, suggesting bare ground in Site 1 had relatively low variation both seasonally and annually compared to other components.



Figure 6. Mean individual ground measured coefficient of variation values, compiled annually and seasonally by component.

Overall, total annual changes were represented by a gradual increase in shrub and sagebrush canopy with corresponding decreases in bare ground, herbaceous, and litter across the four years (Figure 7). Given that water year precipitation increased from 231 mm to 297 mm over this time, this type of component response makes sense for shrub, sagebrush, and bare ground. The slow growth of the sagebrush is to be expected; others have reported that multiple precipitation years may be required to influence overall growth. (Anderson and Inouye, 2001) We expected to see larger annual fluctuations of herbaceous cover, but given the annual growth pattern of many of the herbaceous plants (Bates et al., 2006) (Miller and Eddleman, 2000) it would appear that herbaceous cover in this case is mostly responding to the seasonal precipitation pattern rather than the annual. Total seasonal component change patterns show seasonal fluctuations, especially for the more ephemeral components of bare ground, herbaceous, and litter (Figure 8). These seasonal patterns are also reflected in the annual patterns from the overall two-year annual trends of decreasing bare ground and herbaceous, increasing litter, slightly increasing shrub, and stable sagebrush. The timing of the moisture of the second year (2009) being less abundant in the spring, and more abundant (Figure 8) later in the summer appears to also have influenced the more ephemeral components, with bare ground and herbaceous showing a noticeable fluctuation, and litter a noticeable increase.



Figure 7. Total annual ground-measured percent change compiled by component, 2008–2011



Figure 8. Total seasonal ground-measured percent change compiled by component, 2008–2009

4.2 Satellite Acquisitions

Detecting subtle change with remote sensing requires rigorous processing protocols to overcome inconsistencies in satellite measurements from atmospheric conditions, sun-sensor geometry, geolocation error, variable ground pixel size, sensor noise, vegetation phenology, and surface moisture conditions (Coppin et al., 2004). We paid careful attention to processing protocols developed in this study as well as previous research (Homer et al., 2012) to minimize potential noise differences. The greatest challenge was to ensure that timing of satellite collects were appropriate for groundmeasured phenology conditions. As reported in Table 1, our high-resolution QB satellite collects were less phenologically accurate than LS because the variance from the timing of ground measurements was seven days greater. In this case, we feel the effects were minimal. But because our study area is semiarid with more minimal cloud cover than less arid places, gaining an appropriate phenological series of high-resolution imagery for potential monitoring in other places remains a challenge. Additionally, the need to collect appropriately timed imagery should not outweigh the need for collects with useable view angles. Our experience shows acquiring high-resolution satellite collects with view angles of less than 20° is the most desirable; greater angles make comparison across years or seasons more difficult because of distorted ground geometry. In our case, three QB images had view angles greater than 20 degrees, which required extra processing to maintain consistency. This extra processing is a challenge and does impact product quality, but we recognize that the use of high view angle imagery cannot always be avoided.

4.3 Component change magnitude and direction

With such subtle change amounts and a small sample size of years and seasons, gaining additional understanding of real change versus simple measurement variance is important. We approached this in two ways. First, we examined ground plot deviation using a one-way ANOVA that capitalized on examining the variance of the individual frame measurements for each plot. For annual plots, the mean variation (based on COV) for all pooled plots was 14.8, and the mean COV variation for significant ANOVA pooled plots was 36.4. For seasonal plots, the mean COV variation for all pooled plots was 18.4 and the mean COV for significant ANOVA pooled plots was 35.1. These results confirm that a higher variance threshold was required to achieve significant change, and suggest that annual and seasonal average plot COVs of 35 or higher, on average, indicate that change on the plot is substantial enough to be real.

Second, we pooled ground plots by three categories (all plots, significant ANOVA plots, and significant ANOVA and Slope value plots) with the corresponding sensor-based predictions to understand if our ability to capture change with imagery increased as the significance of change on the ground increased. We anticipated that the sensor-based component predictions would be more successful in capturing groundmeasured change as the reliability and magnitude of change increases. Analysis reveals that as difference trends increase, there is a better correlation with imagery linear slope values (Figure 9), suggesting that as more real change is realized on the ground, sensor component predictions perform increasingly better. QB especially performs well, suggesting a good ability to be a future surrogate for ground measurement, either supplementing or replacing ground plots under some circumstances. LS correlations only improved after pooling for slope significance, suggesting that ground component change needs to happen at both substantial spatial and temporal scales to be reliably detected by LS components.



Figure 9. Three annual mean correlation comparison scenarios of individual ground measured slope values correlated to the corresponding remote sensing prediction slope values by data source. Scenarios include pooling of all ground measured plots, a subset containing only those with significant ANOVA change, and a further subset containing only those both with significant ANOVA change and a significant slope change direction.

4.4 Performance of satellite component predictions

A key objective of this study was to test the utility of continuous field component predictions as a method capable of monitoring subtle change on a sagebrush ecosystem. Especially when this method depends on predictions created from a single base year (2008) or season and then identifies component change on subsequent periods using change vector analysis and regression tree labeling. When compared to corresponding ground measurements by correlation, sensor component predictions performed reasonably well, with mean R values of 0.85 and 0.82 for QB, and 0.77 and 0.73 for LS, all significant at the .01 level (Table 4), successfully demonstrating this objective. We assume QB predictions outperformed LS largely due to the more compatible spatial scale in relationship to the ground plots and spatial ecology and pattern of vegetation in this ecosystem. QB predictions were trained and compared to ground data at the transect level (two transects in every plot) rather than plot level for the training and comparison of LS. The finer spatial scale of QB allowed better tracking of local heterogeneity that was more homogenized at the LS scale. In the future, some additional QB component performance improvement may be realized by training and monitoring at a finer spatial scale than demonstrated by our transect level; however, we speculate that at some level complications of controlling spatial geometry, erratic plot variance, and spurious sensor variance could overwhelm any benefit. (Laliberte et al., 2007) (Ehlers et al., 2003)

When sensor predictions over the entire study area (rather than only at plot level) were compiled as total proportions by component, the correlation of QB and LS proportional area estimates to corresponding ground proportional areas was very high (above 0.99) for both annual and seasonal predictions, showing general compatibility among sources. Additionally, annual and seasonal component change relationships were very similar to plot level polygon measurements, suggesting that sensor predictions over the entire study area remained reliable. For annual predictions, ground-measured proportions exhibited the highest amount of change, with LS second and QB the lowest, with QB also displaying the highest relative error (Table 6). We assume most change

variance is scale related - likely a combination of variance from the ground measurement method and the different ratio of total landscape area covered by ground polygons compared to QB or LS wall-to-wall predictions. Lower change numbers for sensor predictions over ground measurements could also indicate our change method was either too conservative, creating more omission then commission errors, or some ground change was not resolvable by the sensors. For seasonal predictions, LS showed the highest overall mean seasonal change, with ground measurement second and QB the lowest, although LS had higher relative error than QB (Table 7). LS seasonal change values also showed the most variation between components. This amount of change from LS was unexpected, as we anticipated QB to have higher change rates than LS, especially given the consideration that all LS classification and analysis was performed at the much broader landscape level. Our assumption that LS data in general were better calibrated and consistent, and warranted a lower NDVI change threshold than QB (3% vs 5%) for change vector component production appears to be unlikely. This lower threshold likely contributed to the higher LS change values and relative error by allowing more commission error over actual unchanged areas than QB.

4.5 Precipitation correlation results

We recognize that rigorous climate change analysis with remote sensing predictions should ideally be done over spatial and temporal scales larger than our study area. However, this research offered the opportunity to compare annual and seasonal component series measured on the ground and by satellite to newly available DAYMET downscaled precipitation data, providing potential insight into the relationship between component change and precipitation change. Correlations of component change to precipitation change overall were better than expected. When individual component correlations to precipitation were averaged across all components by data source, QB had the highest mean correlations overall at 0.61, with LS having the next highest at 0.54, and ground the lowest at 0.44. The higher mean correlations from the sensor components over the ground measurements is likely due to the ability of their wall-to-wall prediction scale to provide better correlation to the 1-km cell precipitation data than the small footprint of ground plots.

When individual component correlations to precipitation were averaged across all components by season, the annual component mean correlation of 0.64 was much higher than the seasonal component mean correlation of 0.42, suggesting annual component predictions as a whole better reflected precipitation patterns than seasonal predictions. Closer examination of mean correlations pooled by individual annual components reveals mean values ranging from 0.71 for herbaceous to 0.64 for bare ground, 0.63 for shrub and litter, and .059 for sagebrush. The seasonal component mean values ranged from 0.64 for herbaceous to 0.41 for sagebrush, 0.39 for bare ground, 0.37 for litter, and 0.32 for shrub. This suggests that annual components of herbaceous, shrub, and sagebrush, and the seasonal component of herbaceous have the greatest capacity to reflect precipitation patterns. However, component categories still need more in-depth precipitation analysis. For example, when individual component correlations to precipitation are pooled into two categories of ephemeral (bare ground, herbaceous, and litter) and persistent (shrub and sagebrush), the timing of precipitation is a major factor. Persistent components have

higher average correlations when precipitation is calculated as a water year (0.67 as water year and 0.55 as calendar year), and the ephemeral components have higher average correlations when precipitation is calculated as a calendar year (0.69 as calendar year and 0.63 as water year). We assume the higher correlations of persistent components of shrub and sagebrush with water year precipitation better reflect the availability of the potential winter moisture that shrubland physiology is adapted to. Shrubs such as sagebrush can respond to precipitation as far as 2-5 years previous to the growing season. (Anderson and Inouye, 2001) Clearly, more in-depth analysis across larger spatial areas and time frames will be warranted in the future for better predictive analysis, but our initial analysis has shown the potential of establishing a relationship between component change and precipitation change, and should provide confidence at larger scales.

4.6 Implications for sagebrush monitoring

This research demonstrates the ability for multi-scale remote sensing to offer monitoring of gradual change in a sagebrush ecosystem. This has important implications for a widely distributed semiarid ecosystem under threat from multiple disturbance forces creating both abrupt and gradual change. One important implication of our research is the ability of sagebrush fractional components to successfully parameterize change on the landscape. A component metric potentially offers an easily understood, straightforward quantification of the landscape that is measureable over time and offers maximum flexibility to be converted into applications. Perhaps the most far-reaching implication is the demonstrated ability to use sagebrush component predictions trained from a single base year and subsequently projected across many years with change vector analysis (Xian et al., 2012A) (Coppin et al., 2004). For sensors such as LS, with a rich historical archive, this provides further opportunity to compare gradual change rates back in time to causal agents such as climate to further understand potential cause and effect. (Vogelmann et al., 2012) (Xian et al., 2012A) Although, we projected base classifications successfully across 3 years and 5 seasons, we caution that this method likely has a realized decay rate in accuracy from the original classification that would impact results after some number of replications.

Another monitoring implication is the potential ability for high-resolution satellite remote sensing sources such as QB to act as a surrogate to ground measurement. For monitoring to typically be sustained and effective, not only low cost tools and approaches but also mechanisms to maintain consistency are required. Both of these requirements can be difficult to achieve with ground measurements. (Seefeldt and Booth, 2006) The ability to leverage a single year of comprehensive ground collection and image classification across many years of monitoring provides an attractive option to quantify and monitor a landscape. Because of the limited sample size of years and seasons reported here, our research will continue to track additional years to supplement our sample size. Future work is already underway to track precipitation- and temperatureinduced component change many years back in time using the LS historical record.

5.0 Conclusions

Sagebrush ecosystems constitute the largest single North American shrub ecosystem and provide vital ecological, hydrological, biological, agricultural, and recreational ecosystem services. Disturbances have altered and reduced this ecosystem by 50% historically, but climate change may ultimately represent the greatest future risk to this ecosystem. Improved ways to quantify and monitor gradual change in this ecosystem are vital to its future management. Here, we demonstrate the ability to successfully detect gradual change over a 4-year period using continuous field predictions for five components of bare ground, herbaceous, litter, sagebrush, and shrub. Results show that herbaceous and litter exhibited the highest variation for annual and seasonal groundmeasured change, and bare ground exhibited the least. When ground measurements were correlated to corresponding sensor predictions, annual predictions were more highly correlated than seasonal ones, and QB had higher correlation values than LS. Component predictions for the entire study area were also correlated to annual and seasonal DAYMET precipitation amounts. QB had the highest mean correlations to precipitation overall, and herbaceous was the highest performing component overall. Our results demonstrate that regression trees can be successfully used to monitor gradual changing components of a sagebrush ecosystem, demonstrate the ability of high spatial resolution satellite imagery to serve as a reasonable surrogate for repeated ground measurement, and demonstrate the ability of component predictions to respond to changing precipitation. Future work is already underway to track precipitation- and temperature-induced component change many years back in time using the LS historical record, allowing for more comprehensive trend assessment and further analysis of the impact of vegetation component change on ecosystem services.

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CHAPTER 4

FORECASTING SAGEBRUSH ECOSYSTEM COMPONENTS AND GREATER SAGE GROUSE HABITAT FOR 2050, CAPITALIZING ON 28 YEARS OF LANDSAT SATELLITE IMAGERY AND CLIMATE DATA

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Abstract

Sagebrush (Artemisia spp.) ecosystems constitute the largest single North American shrub ecosystem and provide vital ecological, hydrological, biological, agricultural, and recreational ecosystem services. Disturbances have altered and reduced this ecosystem historically, but climate change may ultimately represent the greatest future risk. Improved ways to quantify, monitor, and predict climate-driven gradual change in this ecosystem is vital to its future management. We examined the annual change of Daymet daily gridded surface climate data precipitation and five remote sensing fractional vegetation components (bare ground, herbaceousness, litter, sagebrush, and shrub) from 1984 to 2011 in southwestern Wyoming. Bare ground displayed an increasing trend in abundance over time, and herbaceousness, litter, shrub, and sagebrush showed a decreasing trend. Total precipitation amounts show a downward trend during the same period of time. We established statistically significant correlations between each vegetation component and historical precipitation records using a simple least squares linear regression. Using the historical relationship between vegetation component abundance and precipitation in a linear model, we forecasted the abundance of the vegetation components in 2050 using Intergovernmental Panel on Climate Change (IPCC) precipitation scenarios A1B and A2. Bare ground was the only component that increased under both future scenarios, with a net increase of 48.98 km^2 (1.1%) across the study area under the A1B scenario and 41.15 km² (0.9%) under the A2 scenario. The remaining components decreased under both future scenarios: litter had the highest net reductions with 49.82 km2 (4.1%) under A1B and 50.8 km² (4.2%) under A2, and

herbaceousness had the smallest net reductions with 39.95 km² (3.8%) under A1B and 40.59 km² (3.3%) under A2. We applied the 2050 forecast sagebrush vegetation component values to contemporary (circa 2006) greater sage-grouse (Centrocercus urophasianus) habitat models to evaluate the effects of potential climate-induced habitat change. Under the 2050 IPCC A1B scenario, 11.6% of currently identified nesting habitat was lost, and 0.002% of new potential habitat was gained, with 4% of summer habitat lost and 0.039% gained. Our results demonstrate the successful ability of sagebrush ecosystem components, as predicted by regression trees, to support linear models with precipitation and forecast future component response using IPCC precipitation scenarios. Our approach also enables future quantification of greater sage-grouse habitat, and provides additional capability to identify regional precipitation influence on sagebrush vegetation component response.

1.0 Introduction

Sagebrush (*Artemisia spp.*) ecosystems constitute the single largest North American semiarid shrub ecosystem (Anderson and Inouye 2001) and provide vital ecological, hydrological, biological, agricultural, and recreational ecosystem services (Davies et al., 2007; Connelly et al., 2004; Perfors et al., 2003). However, disturbances such as livestock grazing, exotic species invasion, conversion to agriculture, urban expansion, energy development, and other development have historically altered and reduced these ecosystems (Leonard et al., 2000; Crawford et al., 2004; Davies et al., 2006 & 2007), causing a loss in total spatial extent of about 50% (Connelly et al., 2004; Schroeder et al., 2004; Hagen et al., 2007). Constant perturbations to these systems are disrupting vital biological services, such as providing habitats for numerous sagebrushobligate species. For example, ecosystem decline has severely impacted greater sagegrouse (*Centrocercus urophasianus*) populations across the species range (Connelly et al., 2004; Garton et al., 2011), leaving populations threatened with extirpation in some habitats where they historically persisted (Connelly et al., 2004; Aldridge et al., 2008).

Despite the impacts of past disturbances, climate change may ultimately represent the greatest future risk to this ecosystem (Neilson et al., 2005; Bradley 2010; Schlaepfer et al., 2012a; Schlaepfer et al., 2012b). Both warming temperatures and changing precipitation patterns (such as increased winter precipitation falling as rain) will likely favor species other than sagebrush (West and Yorks 2006; Bradley 2010) and increase sagebrush vulnerability to fire, insects, diseases, and invasive species (Neilson et al., 2005; McKenzie et al., 2004). For each 1°C increase in temperature, approximately 12% of sagebrush habitat is predicted to be replaced by woody vegetation (Miller et al., 2011). Semiarid lands such as sagebrush ecosystems are especially vulnerable to precipitation changes because of low soil moisture content (Reynolds et al., 1999; Weltzin et al., 2003). Variations in precipitation and temperature strongly influence arid and semiarid land plant composition, dynamics, and distribution because water is often the most limiting resource to vegetation abundance (Branson et al., 1976; Cook and Irwin, 1992; Pelaez et al., 1994; Ehleringer et al., 1999; Reynolds et al., 2000). Any substantial changes in global or regional climate patterns that influence precipitation regimes can put these ecosystems at substantial risk (Weltzin et al., 2003; Bradley 2010) by

fundamentally altering biome properties and ecosystem structure (Brown et al., 1997). Developing a better understanding of potential ecosystem component distribution and temporal variation under future precipitation change scenarios can provide critical understanding for management of these lands. Specifically, information about long-term variations of sagebrush ecosystem components can be used to determine the potential relationship between magnitudes of component change and the regional climate.

Remote sensing images that can be interpreted into fractional ecosystem components offer a way to quantify and regionalize subtle climate process impacts on vegetation change in a sagebrush ecosystem across time (Xian et al., 2012a; Xian et al., 2012b; Homer et al., 2013). This process can draw on the Landsat archive, which offers an especially rich source of remote sensing information capable of exploring historical patterns back to 1972, using a global record of millions of images of the Earth (Loveland and Dwyer, 2012). The multispectral capabilities and 30-meter resolution of Landsat are well suited for detecting and quantifying a range of vegetation attributes, as well as for detecting gradual change and the underlying ecological processes (Vogelmann et al., 2012; Homer et al., 2013).

When examining climate change impacts on ecosystem components extrapolated from remotely sensed information, a common challenge is the difference in spatial resolution of the two datasets. To effectively use these data, rescaling of climate data is necessary. Downscaling of climate information such as precipitation can provide the potential for finer scale analysis of smaller regions (Hijmans et al., 2005; Wang et al., 2012). For historical precipitation, longer temporal records available in finer spatial scale products provide new opportunities for defining the relationship between climate change and sagebrush ecosystem change. Specifically, the release of Daymet daily gridded surface climate data (Thornton and Running 1999) provides historical daily precipitation data at 1-km spatial resolution with new opportunities to explore regional scale links of climate change to observed ecosystem change.

For future precipitation projections, advances in climate forecasting also continue to evolve, with the use of atmospheric general circulation models (GCMs). GCMs are commonly used for simulating atmospheric conditions and subsequent future climate response. The IPCC Fourth Assessment Report (AR4) provides climate change projections contributed from different GCMs (IPCC 2007). However, GCMs used in climate change experiments or seasonal forecasts have a typical spatial resolution of a few hundred kilometers for each cell and thus can poorly represent regional climate analysis (Hannah et al., 2002). Global GCM outputs can be to coarse to assess regional impacts on biodiversity, ecosystem services, species distributions, and other landscape related matters (Tabor and Williams 2010; Salathé et al., 2007). Hence, different downscaling techniques have been developed to obtain regional predictions of these climatic changes (Tabor and Williams 2010; Fowler et al., 2007), but the techniques vary in accuracy and output resolution. Because shifts in precipitation may have a greater impact on ecosystem dynamics than rising CO₂ or temperature (Weltzin et al., 2003), downscaled GCMs that accommodate regional processes (e.g., land-water interactions and topography) are especially important when modeling semiarid systems such as sagebrush.

Sagebrush ecosystems contain many wildlife species highly dependent upon the habitat they provide. Wildlife management in the future will require the ability to understand and predict future changes in habitat and the impact on species and populations. Sage-grouse, a sagebrush habitat obligate under consideration for listing as threatened or endangered, is an ideal candidate to evaluate the effects of future conditions based on future habitat scenarios. Sage-grouse experts recognize the need for quantitative monitoring of habitat trends and emphasize the importance of reducing uncertainty about climate change impacts on habitat (U.S. Fish and Wildlife Service 2013). Potential development of successful sage-grouse habitat future scenarios would also allow for application to other species of conservation concern. For the state of Wyoming and in this study area, Fedy et al. (In Review) developed extensive sage-grouse seasonal habitat models using sagebrush ecosystem components as base habitat layers developed from our earlier research (Homer et al., 2012). This provided an ideal opportunity to test potential habitat impacts on sage-grouse as derived from future component trends.

We hypothesized that advancements in capturing gradual change across time using remote sensing components and the downscaling of precipitation could be combined to correlate precipitation trends with vegetation abundance across 28 years. Since precipitation patterns greatly affect vegetation distribution and pattern, we further hypothesized that future scenarios will allow us to quantify changes in vegetation distribution, and the subsequent effect on sage-grouse. We first examined the long-term response of sagebrush ecosystem components to trends in historical precipitation variation and developed linear models explaining this historical relationship. Second, we substituted 2050 IPCC precipitation projections into the linear models to forecast component prediction change in 2050 based on the historical slope of the model. Third, we substituted 2050 sagebrush component values in sage-grouse habitat models to understand the potential impact on habitat quality and quantity.

2.0 Data and Methods

2.1 Overview

We examined the annual change of five sagebrush vegetation components (hereafter called components) from 1984 to 2011. Bare ground, herbaceousness, litter, sagebrush, and shrub were characterized as continuous fields in one percent intervals. We used 2006 and 2007 QB satellite data with coincident field measurements to train 2006 Landsat satellite data to create a 2006 base analysis year. A historical Landsat image was then normalized for every year back to 1984, and compared to the 2006 base to find areas that had spectrally changed. Component predictions were updated in these spectrally changed areas using unchanged 2006 base areas as training sources in regression tree algorithms. Daymet precipitation data for the same time period was downscaled to a 30m grid, and regression analysis was conducted to develop linear models between component estimates and precipitation measurements. We then applied two IPCC precipitation projections to the linear models to produce 2050 predictions for each component. Sagebrush and herbaceousness components for 2050 were used to develop sage-grouse habitat predictions for 2050. We explain each methodological step by section below.

2.2 Study Area

Our study area is located in southwestern Wyoming, United States (Figure 1), and occupies 8330 km2. It contains a range of topography with elevations from 1865 to 2651 m, and slopes up to 48 degrees. It has predominantly sandy soils and contains the Killpecker sand dunes. Vegetation is dominated by sagebrush shrubland, especially in the upland areas, with salt desert shrub species dominating in the lowland and sandy areas. Herbaceous areas range from typical grasses and forbs interspersed among shrubs to subirrigated meadows where a high sub-surface water table in the sand dune areas creates higher than normal biomass productivity for these selected areas. Shrub and herbaceous vegetation occur in a relatively wide range of canopy amounts, with sparser vegetation in the lower elevation southwestern portion of the study area, and denser vegetation in the higher elevation northern portions of the study area. This site is predominantly public land administered by the Bureau of Land Management; therefore, many areas have been historically grazed by cattle for the duration of the summer. We also selected this study area because it contained one of the original eight QB sites used for the 2006 Wyoming sagebrush characterization (called site 1) (Homer et al., 2012) (Figure 1). Site 1 is the location where comprehensive trend analysis has been on-going for many years (Homer et al., 2013).

2.3 Baseline Data Collection

Our approach to calculate component measurements for the base year (2006) and additional years between 1984-2011 required the following steps described in depth

below: 1) Collect and pre-process Landsat data for all years; 2) Calculate vegetation continuous field components for base year (2006); 3) Normalize spectral reflectance of all scenes to base year (2006); 4) Compare yearly Landsat images with the base year to identify pixels that have spectrally changed; and 5) Calculate new component values for spectrally changed pixels from each year.



Figure 1, Study area extent, located northwest of Rock Spring, Wyoming, U.S.A. Note, the small magenta rectangle in the center of the study area is the location of site 1, where intensive monitoring work has been ongoing since 2006 (see Homer et al 2013).

2.3.1 Image Collection and Pre-processing

We acquired eight QB images (64 km² each) distributed across LS path 37/row 31 during the summer of 2006 and 2007 (Homer et al., 2012). For each image, four bands of multispectral information (visible blue, green, red, and near-infrared) were collected at 2.4-m resolution. Imagery was projected to Universal Transverse Mercator (UTM) using a 2x2 bilinear re-sampling kernel. Coincident with image collection, Homer et al. (2012 & 2013) collected field measurements at this site for each component. We estimated percent cover for all components from an overhead perspective (satellite), while stipulating that the total cover of all vegetation and soil components sum to 100%.

We acquired leaf-on (June, July, or August) LS Thematic Mapper (TM) imagery in Level 1T format from 1984–2011 for path 37/row 31 and processed using the automated Landsat Product Generation System (LPGS). We selected LS products that were historically available for the longest span (1984–2011). LS images were converted to at-sensor-reflectance, projected to Albers Equal Area, and terrain corrected (Chander et al., 2009; Xian et al., 2009; Xian et al., 2010).

2.3.2 Component Base Year Predictions

We produced the spatial distributions of five components of sagebrush habitat (bare ground, herbaceousness, litter, shrub, and sagebrush) at one percent intervals for both QB and LS using regression tree models. For the eight QB scenes, ground sampling data were used in regression tree training protocols described in Homer et al. (2012). In order to ensure a rigorous training sample at the LS scale, QB scenes from both 2006 and 2007 were combined to create the 2006 LS base. Adding these sites provided full variation in component ranges across an entire LS path/row and ensured component results were representative of an ecosystem scale classification application. LS base predictions were modeled using three seasons of imagery, coupled with Digital Elevation Model (DEM) and ancillary data (Homer et al., 2012).

2.3.3 Image Normalization, Change Identification, and Prediction

Normalizing the spectral reflectance of the Landsat image dates ensures consistent comparison, which is important for successful trend analysis. We used the following procedures to identify potential change areas and the magnitude and type of change. First, all cloud, cloud shadow, and snow and ice areas were excluded from analysis. Second, a normalization procedure using a linear regression algorithm to relate each pixel of the subject image to the reference image (2006 leaf-on) band by band was conducted (Xian et al., 2012b). Third, potential change area identification was accomplished using a change vector process that compared normalized images to the base image. LS change pixels were identified using thresholds specific to general land cover classes spatially identified from the 2001 National Land Cover Database, similar to Xian et al. (2012b). All cloud and cloud shadow areas were assumed to have no change for that year and removed from the change mask image. Fourth, we assigned a new component value to LS change areas using a regression tree (RT) modeling approach similar to the creation of the 2006 baseline using Landsat at-sensor-reflectance corrected imagery. We identified the candidate training data within the LS base for the RT estimates by excluding potential change pixels via the change mask and binning training pixels using natural breaks in the

histogram. This ensured the RT had similar numbers of training for the full range of each component and good representation of extreme component values. For bare ground, litter, and shrub we created five bins, with three primary bins of low, medium, and high values containing 1000 pixels each, plus two extra bins of 100 pixels with the highest and lowest values. For herbaceousness and sagebrush we created four bins, with three primary bins containing 1000 pixels each of low, medium, and high values, plus one extra bin of 100 pixels with the highest values (a lowest value bin was not required because of the data ranges). For each component, we randomly selected training pixels (sample points) from the entire pool of candidate pixels.

Finally, we developed predictions quantifying the spatial distribution and perpixel proportion of each component as a continuous variable using regression models for all change pixels in the LS image. Baseline predictions for spectrally unchanged pixels were not modeled and left as original predictions from the base year. Using the change mask created from the change vector process, we then applied each of the change pixel prediction values over the base prediction, with the no-change pixels retaining the prediction value from the base prediction, and only the change pixel areas updated for each new imagery date (Xian et al., 2012b). For study area wide change analysis, we compiled predictions by total area of change (the areal proportion of the component of each cell into a total area summary value) for each component for each year across the study area on areas that were not masked in any year (pixels that were pure across all 28 years). We also calculated the mean year-to-year percent change and linear trend. Annual component proportions and annual water year mean values were correlated using a Pearson's correlation.

2.4 Climate data processing, historical climate data

The Daymet model is a collection of algorithms and computer software designed to interpolate and extrapolate daily meteorological observations to produce gridded estimates of daily weather parameters over the conterminous United States, Mexico, and southern Canada (Thornton 1999). The required model inputs include a digital elevation model and observations of maximum temperature, minimum temperature, and precipitation from ground-based meteorological stations. The Daymet method was developed at the Oak Ridge National Laboratory and is based on the spatial convolution of a truncated Gaussian-weighting filter run with the set of station locations. Sensitivity to the heterogeneous distribution of stations in complex terrain is addressed using an iterative station density algorithm. For our analyses, we considered Daymet products of minimum and maximum temperature, precipitation, humidity, and incident solar radiation produced on a 1 km x 1 km gridded surface. We summarized the daily gridded surfaces into monthly totals (precipitation) or averages (temperature), and then compiled monthly precipitation data into water year totals (October to September) for each year between 1984 and 2011 within our study area. We re-projected all data to match the map projection used for the sagebrush products and re-sampled the 1-km grids to 30-m spatial resolution using the bilinear interpolation method.

2.5 Climate data processing, future predictions

We obtained future precipitation data from the IPCC Fourth Assessment Report (IPCC, 2007). We evaluated 2050 precipitation data from three global climate models including the Geophysical Fluid Dynamics Laboratory Coupled Climate Model 2.1(GFDL-CM2.1) (Delworth et al., 2004), the National Center for Atmospheric Research Community Climate System Model 3.0 (NCAR-CCSM3.0) (Collins et al., 2005) and the United Kingdom Met Office Hadley Center Coupled Model 3.0 (UKMO-HADCM3) (Gordon et al., 2002). We evaluated two of the four family scenarios with these models: A1B (economic growth with balanced energy development) and A2 (high population growth). Future climate changes under the A1B and A2 scenarios will result in substantial increases in surface temperature: 1.7 - 4.4 °C for A1B and 2.0–5.4 °C for A2. We excluded the other two family scenarios from our analysis because our downscaled precipitation data were not available for the B2 family and we judged the B1 family represented an unlikely scenario for this area. We used downscaled 30 arc-second GCM model predictions for the three models mentioned above for both future climate change scenarios. These downscaled data were created using the Delta method (Hijmans et al., 2005; Ramirez-Villegas and Jarvis 2010), which we downloaded from the CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) (www.ccafts-climate.org). We re-projected the data to the same projection as the sagebrush components and resampled to 30 m using the Bilinear Interpolation method. We organized the original data in monthly precipitation, which was recompiled into annual precipitation and clipped to fit our study area.
2.6 Future component change predictions

We developed future predictions for five sagebrush components by first exploring historical data correlations between several climate indices and sagebrush components to understand correlation potential at the study area scale. We then developed the most promising climate indices (annual precipitation) as a linear model at the single pixel level and subsequently applied these relationships to future climate precipitation scenarios. These steps are outlined below.

2.6.1 Linear regression

We conducted correlation analysis between the study area mean fractional cover of sagebrush components (dependent variable) and several climate indices (independent variables), including total annual precipitation, annual mean temperature, total seasonal precipitation, total snow water equivalent, and mean incident solar radiation. Overall, the fractional cover of sagebrush components and annual (water year) precipitation had the highest correlation and was selected for further analysis. Therefore, linear regression models relying on the least squares estimator were developed using the fractional cover of the five sagebrush components and annual precipitation at the pixel level. For all annual records in a pixel location, the linear regression approach fits a straight line through the set of n points that minimizes the sum of squared residuals (deviation of observed and theoretical values):

 $Y = a + bX \tag{1}$

where X is an independent variable (e.g., annual precipitation), Y is a dependent variable (sagebrush component), b is the slope of the fitted line (equal to the correlation between Y and X corrected by the ratio of standard deviations between Y and X), and a is the y-intercept term.

Five linear regression analyses were conducted independently using data between 1984 and 2011 including bare ground cover and annual precipitation, herbaceous cover and annual precipitation, litter cover and annual precipitation, sagebrush cover and annual precipitation, and shrub cover and annual precipitation. Our null hypothesis is that there is no significant linear relationship between the sagebrush components and precipitation. We tested our null hypothesis using a two-sided t-test for each component, which can reveal both positive and negative correlations between X and Y in Eq. (1). We evaluated the p-value for three significance levels: 0.05 , <math>0.01 , and p ≤ 0.01 and selected 0.05 as the significance threshold. Only pixels that haveeither significant positive or negative correlations were retained for calculating the future change prediction at each individual pixel level. For pixels with non-significant correlations, we developed a modified linear regression model based on the average slope value of all non-significant pixels. This ensured that extreme changes in future precipitation values occurring over non-significant pixel areas would still be represented in the future component forecasts.

2.6.2 Future change prediction

Future change predictions for each sagebrush component were performed using component specific linear regression equations:

$$Y_{(i,j)}(k,2050) = Y_{(i,j)}(k,2006) + b_{(i,j)}(k)(X_{(i,j)}(2050) - X_{(i,j)}(2006))$$
(2)

where, i and j represent pixel locations, Yi,j(k, 2050) represents the fractional cover of the sagebrush component k for a pixel located at i and j, b(k) is a slope for the component k, Xi,j(2050) is the annual precipitation, and Xi,j(2006) is the annual precipitation in 2006. The 2050 annual precipitation predicted by numerical models in the study area was used as the independent variable in Eq. (2) to project the factional covers of the five sagebrush components to 2050. For pixels that have non-significant negative correlation for bare ground and positive correlations for other components, a mean slope for the entire area is used to replace bi,j(k) in Eq. (2). The non-significant mean correlation slope was chosen in Eq. (2) to capture expected minor changes as well. Future precipitation change may not follow the exact same patterns in areas that experience significant correlations. The use of mean slope for these pixels will ensure that impacts of more extreme patterns of future precipitation will be captured in the future component projections. We developed predictions using annual precipitation amounts from each of the two climate change scenarios.

2.7 Sage-grouse habitat models and 2050 habitat predictions

Contemporary models evaluating sage-grouse habitat requirements have recently been developed for the state of Wyoming (Fedy et al., In Review). Sage-grouse response to anthropogenic, abiotic, terrain, and vegetation characteristics was assessed using Generalized Linear Model (GLM) Resource Selection Functions (RSFs; Manly et al. (2002)) applied to telemetry data from multiple studies across the state. These models predict probability of selection for any given pixel (30m) on the landscape, and this continuous surface is subsequently thresholded into a binary surface depicting habitat and non-habitat for sage-grouse (see Fedy et al., In Review for details). Vegetation layers evaluated were the same base year (2006) sagebrush components used for climate analyses presented here, making for relatively simple evaluation of future changes in sagebrush components on sage-grouse habitat. Fedy et al. (In Review) developed models for nesting, late-summer, and winter, using different scales (moving windows) to characterize vegetation components. Here, we evaluate only nest and summer models, given the difficulties with development of winter models (see description in Fedy et al., In Review).

In the original statewide sagebrush component products, edge matching in Landsat overlap zones and standardization was required to stitch together models developed for individual Landsat scenes (Homer et al., 2012). Our target study area was partially within the overlap zone of Landsat Path 37/Row 31 and Path 37/Row 32, so for this study we chose to develop historical climate projections based on data from a single scene (Path 37/Row 31). This allowed for consistency with the climate analyses using

spectral information from one LS scene over time. As a result, we reapplied the original GLM sage-grouse RSF habitat model equations using base layer component values for each pixel developed from the single Landsat scene presented here. This resulted in a consistent sage-grouse base year (2006) habitat model to build upon for projections. We first regenerated the appropriate model covariates required for the sage-grouse model using the same spatial extent (moving window) found to be important in the original sage-grouse models. For instance, if mean cover of big sagebrush (Artemisia tridentata ssp.) over a 6.4-km radius window was in the original model (Fedy et al., In Review), we took the new pixel estimates for the 2006 base year generated from the single Landsat Path/Row sagebrush component models and re-calculated the mean values over the same spatial extent. This allowed for reapplication of the model using modified inputs, generating consistent and compatible models that identified sage-grouse habitat requirements for nesting and late summer. We applied the thresholding values used in the original models to develop a binary habitat/non-habitat map. Original habitat models were developed at two scales (patch and landscape; see Fedy et al. In Review), and coefficients for all sagebrush habitat components contained within the original logistic regression RSF model responses are shown in Table 1. We followed the same steps to develop the predicted 2050 sage-grouse habitat models, simply substituting in 2050 habitat component predictions and generating the appropriate moving window covariate where necessary.

Table 1. Nesting and summer habitat logistic regression model coefficients and standard errors (in brackets) used to predict effects of changes in sagebrush habitat components due to climate change in 2050. Many variables were included in the original path and landscape models (see Fedy et al. *In Review*). These were also applied to future scenarios analyses developed here, however only the sagebrush habitat components within those models were changed, which are shown here.

Sage- Grouse	Nesting Habitat		Summer Ha	abitat
Habitat Model Covariates	Patch	Landscape	Patch	Landscape
Mean SB all species ^a	0.210 (0.020)			
Mean SB all species ^b			0.065 (0.010)	
SD SB all species ^c			-0.011 (0.030)	
Mean SB all species ^d		0.224 (0.020)		
Mean SB all species ^e				0.086 (0.010)
SD SB all species ^f				0.090 (0.030)
Mean Herbaceous ^g	0.015 (0.010)			
SD Herbaceous ^h	0.165 (0.040)			

^a mean cover of all sagebrush species estimated over a 564 m radius moving window

^b mean cover of all sagebrush species estimated over a 45 m radius moving window

^c standard deviation of mean sagebrush cover (all species) estimated over a 45 m radius moving window

^d mean cover of all sagebrush species estimated over a 1500 m radius moving window

^e mean cover of all sagebrush species estimated over a 3200 m radius moving window

^f standard deviation of mean cover of all sagebrush species estimated over a 3200 m radius moving window

^g mean cover of herbaceous vegetation estimated over a 564 m radius moving window

^h standard deviation of mean cover of herbaceous vegetation estimated over a 564 m radius moving window

3.0 RESULTS

3.1 Historical component and precipitation change and correlation

We measured annual change in five sagebrush ecosystem fractional vegetation components (bare ground, herbaceousness, litter, sagebrush, and shrub) over 28 years (1984–2011) from the base year of 2006. Measured areas needed to be available in all 28 years (if cloud covered in any one year, this area was excluded from all years) with 40% of the study area (3,288 km²) available in all years and widely distributed. Bare ground is by far the most dominant component of the landscape with mean proportion coverage of 59.1%, followed by litter at 16.16%, herbaceousness at 13.56%, shrub at 11.21%, and sagebrush at 9.4% (Table 2). When analyzed for variation between individual years, bare ground displayed the highest annual variation with a mean annual change of 0.54%, and sagebrush the lowest at 0.17% (Table 2). When analyzed across all 28 years, bare ground showed an overall increasing trend in abundance, with herbaceousness, litter, shrub, and sagebrush showing a decreasing trend. Litter displayed the most obvious decreasing trend.

We calculated mean annual water year precipitation over the entire study area. Precipitation varied from a low of 125 mm in 2001 to a high of 404 mm in 1986 (Figure 2). Overall, there is a downward trend in the historical amount of precipitation received (Figure 2). We conducted Pearson's correlation analysis between component study area means and annual precipitation study area means. Correlations (r's) ranged from 0.56 for herbaceousness, to 0.48 for sagebrush, 0.43 for shrub, 0.42 for litter, and 0.38 for bare ground. Herbaceousness and sagebrush correlation values were significant at the 0.01 level, and all others significant at the 0.05 level.

Table 2. Total annual percent proportional cover change compiled as a total study area value, by component. This metric was calculated using only valid pixel values present in all 28 years. If cloud cover precluded the inclusion of valid pixels from any year, that area was excluded from all years. The resulting area represented here consisted of 39% of the study area $(3,288 \text{ km}^2)$.

X	Components – Percent Coverage							
Year	Bare Ground	Herbaceous	Litter	Sagebrush	Shrub			
1984	58.96%	13.53%	16.19%	9.49%	11.24%			
1985	59.43%	13.47%	16.05%	9.38%	11.15%			
1986	56.23%	13.72%	17.61%	10.31%	12.22%			
1987	59.85%	13.72%	15.70%	9.21%	10.96%			
1988	59.46%	13.44%	16.02%	9.29%	11.12%			
1989	59.24%	13.55%	16.07%	9.34%	11.14%			
1990	59.43%	13.49%	16.08%	9.33%	11.15%			
1991	59.50%	13.52%	15.97%	9.30%	11.11%			
1992	59.17%	13.61%	16.08%	9.38%	11.18%			
1993	59.10%	13.67%	16.08%	9.48%	11.23%			
1994	58.91%	13.44%	16.27%	9.49%	11.37%			
1995	59.00%	13.75%	16.39%	9.48%	11.33%			
1996	59.23%	13.48%	16.10%	9.40%	11.17%			
1997	59.00%	13.66%	16.29%	9.42%	11.27%			
1998	59.52%	13.71%	15.92%	9.41%	11.10%			
1999	59.15%	13.72%	16.13%	9.45%	11.22%			
2000	59.39%	13.26%	16.03%	9.31%	11.12%			
2001	58.95%	13.52%	16.06%	9.33%	11.20%			
2002	59.19%	13.57%	16.09%	9.33%	11.08%			
2003	59.47%	13.69%	15.94%	9.26%	11.05%			
2004	58.16%	13.90%	16.69%	9.51%	11.45%			
2005	59.19%	13.49%	16.02%	9.26%	11.10%			
2006	59.35%	13.01%	15.98%	9.07%	11.03%			
2007	59.31%	13.56%	16.06%	9.43%	11.12%			
2008	59.22%	13.54%	16.06%	9.26%	11.11%			
2009	59.06%	13.62%	16.20%	9.48%	11.24%			
2010	59.28%	13.57%	16.07%	9.30%	11.08%			
2011	59.04%	13.49%	16.20%	9.48%	11.24%			
Mean	59.10%	13.56%	16.16%	9.40%	11.21%			
Standard								
Error	0.0012	0.0003	0.0006	0.0004	0.0004			
Mean Annual								
Change (%)	0.54%	0.18%	0.29%	0.17%	0.19%			



Figure 2, Mean annual precipitation from 1984 to 2011 over the study area calculated from Daymet data by water year, with the linear trend line.

3.2 2050 Component forecasting

We excluded non-sagebrush component landscapes within the study area from future component forecasting (areas permanently converted to agriculture and urban land use), leaving 91% (7,580 km²) of the study area for analysis. We calculated future change predictions for each sagebrush component 30-m pixel displaying a significant linear regression (P < 0.1) result between historical component and precipitation change. Most pixels did not have a significant linear regression and remained unchanged in the 2050 predictions (Table 3). For bare ground–precipitation regression, the number of pixels that had negative correlations was about three times larger than the number of pixels that had positive correlations. For other components, two to three times more pixels had positive correlations than those that had negative correlations. Herbaceous cover had the lowest proportion of pixels qualifying for future updating at 22.3%, and litter had the highest

proportion of pixels qualifying for future updating at 24.6% (Table 3).

Table 3. The percentage of the total pixels that presented significant correlations (p < 0.1) to annual precipitation, listed by component. These amounts include both positive and negative correlations.

Component	% Total pixels with significant positive correlation	% Total pixels with significant negative correlation	% Total pixels with both positive and negative correlations
Bare Ground	6.1%	18.3%	24.4%
Herbaceous	12.8%	9.5%	22.3%
Litter	18.8%	5.8%	24.6%
Sagebrush	18.6%	5.9%	24.5%
Shrub	17.4%	6.7%	24.1%

We evaluated 2050 precipitation data from three global climate models (GFDL-CM2.1, NCAR-CCSM3.0, and UKMO-HADCM3) across two of four family scenarios (A1B and A2) (Table 4). The NCAR-CCSM3.0 model presented the most divergent precipitation amounts between A1B and A2 (Table 4) and was selected for linear modeling implementation. Forecast precipitation amounts from two 2050 IPCC scenarios were input into each significant linear pixel equation and the influence on pixel component surfaces in 2050 was calculated and subsequently compared to the 2006 base component predictions. Bare ground was the only component that increased under both future scenarios, with a net increase of 48.98 km² (1.1%) across the study area under the A1B scenario and a net increase of 41.15 km² (0.9%) under the A2 scenario (Table 5,

Figures 3 & 4). The remaining components decreased under both future scenarios, with litter having the highest net reductions under both scenarios (A1B scenario at 49.82 km² (4.1%), and the A2 scenario at 50.8 km² (4.2%), and herbaceousness the smallest net reductions under both scenarios (A1B scenario at 39.95 km² (3.8%), and the A2 scenario at 40.59 km² (3.3%) (Table 5, Figures 3 & 4).

Table 4. The comparison of 2050 mean study area precipitation projections calculated for two families of three IPCC models. For comparison, the total mean study area precipitation historically from 1984–2011 was 263 mm.

MODEL	2050 SCENARIO		
	A1B	A2	
NCAR-CCSM3.0	228 mm	216 mm	
GFDL-CM2.1	236 mm	230 mm	
UKMO-HADCM3	228 mm	229 mm	

Table 5. Positive and negative total component change amounts in km² for 2050 IPCC A1B and A2 scenario forecast change results compared to the 2006 component base predictions.

	A1B Scenario			A2 Scenario			
Component			Net			Net	
component	- Change	+ Change	Change	- Change	+ Change	Change	
	(km²)	(km²)	(km²)	(km²)	(km²)	(km²)	
Bare Ground	-2.21	51.19	48.98	-1.98	43.14	41.15	
Herbaceous	-43.47	3.52	-39.95	-44.69	4.09	-40.59	
Litter	-51.68	1.86	-49.82	-52.98	2.18	-50.80	
Sagebrush	-46.95	1.21	-45.74	-47.68	1.44	-46.24	
Shrub	-45.99	1.17	-44.83	-46.78	1.40	-45.38	



Figure 3, Spatial distribution of component prediction change between 2006 and 2050 for the A1B scenario across the entire study area. Component reductions are represented in red and orange tones and increases in green tones.



Figure 4. Spatial distribution of component prediction change between 2006 and 2050 for the A2 scenario across the entire study area. Component reductions are represented in red and orange tones and increases in green tones.

3.3 Sage-grouse habitat model forecasting

We assessed two sage-grouse seasonal habitat scenarios: nesting and summer habitat. In 2006, identified nesting habitat covered 3,059 km², or roughly 37% of the sage-grouse study area where we had data available (Table 6), and summer habitat covered roughly 21% of the sage-grouse study area (~1,669 km²; (Table 6)). For nesting habitat, the 2050 model for IPCC A1B habitat estimates applied to the sage-grouse model had a loss of 355 km² of adequate sage-grouse habitat, resulting in an 11.6% loss of habitat identified in 2006, and the IPCC A2 had a loss of \sim 361 km² of sage-grouse habitat, or 11.8% (Table 6, Figure 5). For summer habitat, the 2050 model for IPCC A1B scenarios modeled predicted a loss of $\sim 67.5 \text{ km}^2$ of habitat identified in 2006 (~4.0% loss), and the IPCC A2 had a loss of ~68.1 km^2 of habitat identified in 2006 (~4.1% loss; (Table 6, Figure 6)). In both IPCC scenarios for each life stage, a small number of pixels across the study area improved in habitat quality, but the gain in identified habitat was less than 0.08 km² in all cases (Table 6). Habitat losses can be seen in Figures 5 & 6 in areas surrounding 2006 predicted habitat. These losses are related to the sage-grouse models capturing habitat characteristics across larger landscapes (moving windows), such as selection for high mean sagebrush cover over a 1,500-m radius window.

Table 6. Total amount of study area that contained sage-grouse nesting and summer habitat in the 2006 base year and in 2050 using sagebrush habitat components from two different climate scenarios (A1B and A2). Habitat losses are based on 2050 landscapes relative to identified habitat in the 2006 base year. Habitat gains represent novel areas (pixels) in the 2050 landscape predicted to be suitable for sage-grouse, whereas habitat losses represent areas that were identified as habitat in 2006 but in 2050 are no longer habitat.

	Nesting			Summer		
	2006	2050 (A1B)	2050 (A2)	2006	2050 (A1B)	2050 (A2)
Predicted Habitat (km ²)	3,059.876	2,704.859	2,699.100	1,668.902	1,602.087	1,601.553
Habitat Gain (km ²)		0.077	0.124		0.644	0.713
Habitat Loss (km ²)		355.093	360.900		67.460	68.063



Figure 5. Predicted changes in sage-grouse nesting habitat from 2006 to 2050 from climate scenerio A1B. Changes are based on the original sage-grouse habitat models from Fedy et al. (In Review) for the 2006 base year, which were then predicted to 2050 based on changes in sagebrush vegetation characteristics linked to the (a2) climate projection scenario. A small number of pixels changed to habitat in 2050 habitat (blue), which are difficult to see at the mapped scale. The no habitat class represents areas where one or more sage-grouse model data inputs were not available, preventing model prediction.



Figure 6. Predicted changes in sage-grouse summer habitat from 2006 to 2050 from climate scenerio A1B. Changes are based on the original sage-grouse habitat models from Fedy et al. (In Review) for the 2006 base year, which were then predicted to 2050 based on changes in sagebrush vegetation characteristics linked to the (a2) climate projection scenario. A small number of pixels changed to habitat in 2050 habitat (blue), which are difficult to see at the mapped scale. The no habitat class represents areas where one or more sage-grouse model data inputs were not available, preventing model prediction.

4.0 DISCUSSION

The sagebrush ecosystem is a moisture limited system, and precipitation change is the major driver of vegetation change (Lauenroth and Sala 1992; Bates et al., 2006; West and Yorks 2006; Davies et al., 2007). This is supported by our results showing significant relationships between remote-sensing-derived sagebrush ecosystem components predicted by regression trees and changing precipitation patterns. Our development of per pixel models that capitalized on historical remote sensing and precipitation for forecasting future component amounts is an encouraging new approach to quantify the impacts of climate change. Our models predicted the portions of the landscape that will undergo changes in sagebrush habitat components by 2050. Of specific concern is that the estimation from sage-grouse habitat models applied to these altered future landscapes predicts as much as 11% of sage-grouse nesting habitat and 4% of summer habitat will be lost. Given declining sage-grouse populations suffering from other habitat degradation forces, a potential additional 11% loss of future habitat from climate change could be very detrimental to some sage-grouse populations. We discuss the different stages of our component prediction and modeling approach in detail below.

4.1 Remote sensing trend analysis

Detecting subtle trends with remote sensing requires rigorous processing protocols to overcome inconsistencies in satellite measurements from atmospheric conditions, sun-sensor geometry, geolocation error, variable ground pixel size, sensor noise, vegetation phenology, and surface moisture conditions (Coppin et al., 2004). Our rigorous normalization procedures developed in other research (Xian et al., 2009) support the detection of subtle precipitation differences expressed through component prediction response. Often, the greatest challenge with trend analysis is to ensure historical satellite collects represent similar phenological periods. If not, detected remote sensing differences are driven by phenological noise rather than true annual change. In this case, Landsat image dates across the 28 years had a mean deviation of 20.2 days (SE 2.42 days) from the base year; 2007 had the earliest capture difference from the base at June 2^{nd} (45 days), and 1986 had the latest capture difference from the base at August 27^{th} (39 days). Component trends are seasonally influenced, especially the more ephemeral components of bare ground, herbaceousness, and litter (Homer et al., 2013). Our Landsat image dates were not ideal for every year, and some seasonal phenological variation likely influenced our trend analysis. However, correlation values of annual precipitation to shrub and sagebrush were comparable to the more ephemeral components of herbaceousness, bare ground, and litter, suggesting we captured legitimate annual trends for all the components. It is worth noting that, even with the semiarid nature of our study area producing minimal historical cloud cover, obtaining historical imagery with ideal phenology still presented a challenge.

4.2 Component prediction change

Recent research has demonstrated the utility of continuous field component predictions for monitoring subtle change in a sagebrush ecosystem, when predictions are created from a single base year and then change in other periods is accomplished using change vector analysis and RT labeling (Xian et al., 2012a; Xian et al., 2012b; Homer et al., 2013). Here, we expand upon that work and demonstrate the utility across additional time periods and a larger spatial extent. Total annual proportional change amounts for each component were relatively modest (Table 1), with mean annual change percent values varying from a high of 0.54% for bare ground to a low of 0.17% for sagebrush. These amounts are fairly similar to mean annual Landsat component change reported in other work (Homer et al., 2013) for sagebrush, shrub, and litter, but substantially lower than amounts reported for bare ground and herbaceousness components. We assume the much longer time period represented in this work with many more years in the sample and a larger study area with more diverse landscapes likely account for the smaller mean annual change amounts. However, the magnitude of annual change still looks reasonable when considering we are focused on capturing component change driven only by changing precipitation.

Further evidence that component change magnitudes are meaningful comes from the correlation of mean annual component change proportions to mean annual precipitation. The mean correlation (r) across all five components was 0.45, demonstrating substantial precipitation change patterns are reflected in our annual component predictions. Of special note, the two components used in the sage-grouse habitat models had the highest correlation with precipitation, 0.56 for herbaceousness and 0.48 for sagebrush. These results suggest annual component performance is robust enough to reasonably capture vegetation response to precipitation change and subsequently lay a credible foundation for future forecasting.

4.3 Precipitation trends

Annual precipitation varies widely in this semiarid environment (Caldwell 1979; West 1999; Bates et al., 2006). However, there has been a downward trend in precipitation amounts across the study area over the last 28 years (during the last two unreported years, 2012 and 2013 that pattern has continued) (Figure 2). Forecast precipitation amounts in 2050 from the two IPCC projections suggest this pattern will continue, with a mean forecast of 228 mm under the A1B scenario and 216 mm under the A2 scenario, remaining consistent with the historical trend.

Because sagebrush ecosystems are typically moisture limited and dependent upon winter snowfall for adequate moisture penetration into the soil, the combination of reduced moisture overall and the shift in timing of moisture reception creates greater risk of disruption of ecosystem processes for this system (Bates et al., 2006; Davies et al., 2007). Understanding local and regional variations in potential moisture availability becomes more important than ever. The availability of downscaled Daymet data provides additional opportunities to explore regional precipitation and component relationships. Converting Daymet data to 30-m grid cells is likely pushing the limit of its spatial performance (Daly 2006); however, because our study area is relatively flat and does not contain large water bodies, downscaling the climate data is done under a scenario where it can be effective (Daly 2006). Further, although there are likely multiple driving forces between component and precipitation response, our results demonstrate there is indeed a substantial quantifiable relationship between components and precipitation change that can be captured with a model.

4.4 2050 future component predictions

Our historical linear trend analysis revealed that approximately one quarter of all pixels in the study area possess significant positive or negative correlations between precipitation change and component change. Since this analysis represents historical change patterns, such patterns may persist in the future. We also needed to account for future extremely low or high magnitude GCM predictions for precipitation that might occur in areas not containing significant correlations between historical patterns of precipitation and sagebrush components. If future change predictions were processed only in the significant correlated areas, impacts associated with extreme precipitation patterns would be ignored in non-significant areas. Therefore, in our future predictions, we used a study area average slope value for pixels that have non-significant correlations (negative for bare ground and positive for other components) to ensure some opportunity exists to quantify future component change also for these areas. This especially ensures the model prediction can capture the impact of extreme patterns of future precipitation on sagebrush components both on significant and non-significant patterns of future precipitation on sagebrush components both on significant and non-significant patterns of future precipitation on sagebrush components both on significant and non-significant patterns of future precipitation on sagebrush components both on significant and non-significant patterns of future precipitation on sagebrush components both on significant and non-significant patterns of future precipitation on sagebrush components both on significant and non-significant patterns of future precipitation on sagebrush components both on significant and non-significant patterns of patterns of future precipitation on sagebrush components both on significant and non-significant patterns of patterns patterns of patterns patterns

The total 2050 predicted component mean study area change is relatively modest for both IPCC scenarios (Table 5). However, it is important to keep in mind that these total change amounts are not evenly distributed across the study area. Only about one quarter of the total pixels qualified for calculating a different prediction for 2050 (Table 2), and most changed by relatively small increments of 1–2% from the 2006-based prediction (Figure 7). This reveals that the slope of the individual linear equations was often quite gradual, which is expected when reflecting climate change. However, this also suggests that in an ecosystem with such wide annual variation, exploring the capability of more complex linear or nonlinear models may be warranted. Some pixels had more dramatic liner equation slopes resulting in change amounts greater than 1%. These pixels were typically distributed in more rare, unusual, or vulnerable parts of the landscape defined by topography, soils, or other factors. Having greater change happen in these more unusual or vulnerable areas also seems reasonable, as reducing precipitation patterns would likely have a greater influence on the more vulnerable topographical and soil-related areas. Producing successful remote sensing predictions capable of capturing such small increments of change in a regionally credible way provides an opportunity to monitor incremental vegetation and bare ground change that would likely occur with changing precipitation. Although component change amounts in the 2050 scenarios are relatively subtle, they are still substantial, especially when considering that this study area is in the core range of the sagebrush ecosystem (Knick et al., 2003; Bradley 2010) and currently thought to be one of the least vulnerable parts of the sagebrush ecosystem to climate change (Bradley 2010). If changes of this magnitude are predicted in a core part of the ecosystem, it would suggest much greater change is likely in peripheral areas.





Figure 7. The distribution of per pixel change magnitudes for all 2050 components summed across the study area, by scenario.

Our approach of developing remote sensing components across 28 years using the historical Landsat archive provides a great example of the current opportunities remote sensing archives can provide. The ability to study component change using long-term

observations in conjunction with records of precipitation change provides an opportunity to infer empirical patterns without developing complex mechanistic models. This provides opportunities to develop useful projections of component change across large areas in a relative quick and affordable way. However, conclusions from this type of forecasting should be considered tentative and recognize that forecasting future climate scenarios contains significant uncertainties (Weltzin et al., 2003; Walther 2010). Climate change drivers are complex and climate extrapolations into the future that are dependent upon linear models can be over simplistic because future responses of vegetation to climate will likely not be always linear (Weltzin et al., 2003, Walther 2010). However, projecting inference-based precipitation change through sagebrush component response provides a new capability to regionalize precipitation patterns and component response and define areas and magnitudes of potential risk. This ability to quickly and affordably quantify future component change could prove invaluable to land managers faced with the need to make localized decisions in order to realize long-term regional benefits. Work such as this provides patch level feedback, and the component-based approach provides unlimited opportunities to apply these more generic products to specific applications.

Our IPCC GCM projections may also contain some regional error from the downscaling method. However, further interpolating surface climate is most likely to introduce biases in highly heterogeneous landscapes where extreme topography causes considerable variation over relatively small distances, a situation which does not occur in our study area (Daly 2006). Regardless, because there are likely uncertainties introduced in our results from downscaling the future precipitation data, we recommend further investigation to assess potential uncertainties caused by future precipitation downscaling on sagebrush component change predictions.

4.5 2050 sage-grouse habitat scenario modeling

Research addressing the effects of climate change on sagebrush habitats has only recently been explored (see Perfors et al., 2003; Neilson et al., 2005; Schlaepfer et al., 2012b; Schlaepfer et al., 2012c; Xian et al., 2012a). While range-wide population extirpations of greater sage-grouse have been loosely correlated with the frequency of severe droughts (Aldridge et al., 2008), the consequences of these changes for sagegrouse have not been fully explored. Our forecasted changes in future sagebrush habitat conditions present a unique opportunity to evaluate the consequences of climate-induced changes on habitat quality for sage-grouse. In 2006, we predicted 3,059 km² and 1,669 km^2 of our 7,580 km^2 study area would be suitable sage-grouse habitat for nesting, and summer, respectively (Table 6). Our habitat models predicted that 45 km^2 of this area would experience decreases in sagebrush cover, and herbaceous cover could also decline in $\sim 40 \text{ km}^2$ of habitat, using either climate scenario (Table 6). Given sage-grouse in our study area (Fedy et al., in Review) and across their range select for areas of increased sagebrush cover (Aldridge and Boyce 2007; Aldridge et al., 2008; Doherty et al., 2010; Aldridge et al., 2012) and also select for increased herbaceous cover (Crawford et al., 2004; Aldridge et al. 2008; Fedy et al., In Review), one might expect a small decline in predicted sage-grouse habitat through 2050 as abundance of these components decrease. Predicted losses of ~12% of sage-grouse nesting habitat and ~4% of summer habitat from 2006 to 2050 (Table 6, Figures 5 & 6) due to climate alone are significant. Given our

study area occurs in some of the most intact sagebrush habitats that remain (Bradley 2010), climate effects on sage-grouse habitat could be more severe in fringe populations.

Sage-grouse face numerous current and future threats to their habitats, some of which include energy development (Braun et al., 2002; Aldridge and Boyce 2007; Walker et al., 2007), invasion by exotic plants (Knick et al., 2004, Evers et al., 2013), fire (Connelly et al., 2000, 2004; Evers et al., 2013), and agricultural conversion (Connelly et al., 2004). Independent of these added environmental stressors, sage-grouse population might very well withstand habitat losses due to climate change alone. Yet with impacts of rapid expansion of energy development in eastern populations (Kiesecker et al., 2011) and ecosystem changes due to fire and exotic invasive plants in western populations (Connelly et al., 2004), the cumulative impacts of multiple change agents (including climate) may have extensive consequences for sage-grouse populations across the species range. Smaller populations such as those on the fringe of the species range that have reduced connections to other populations may be at increased risk (Aldridge et al., 2008), and climate change could exacerbate those local extirpations. Clearly, effective management decisions for sage-grouse, like those using core areas for the conservation of sage-grouse (Doherty et al., 2011), should begin to consider potential effects of climate change on sage-grouse and their habitats. Seasonal habitat models are being developed for many sage-grouse populations across the species range, similar to those used here (Fedy et al., In Review). Thus, an opportunity exists to apply our relatively simple regression approaches to other areas to understand potential future climate impacts on sagebrush habitats. These approaches should be applied across larger spatial extents (i.e.,

the state of Wyoming), which would help to better understand both quantitatively and spatially how future climate change will impact sage-grouse and their habitats.

5.0 CONCLUSIONS

Sagebrush ecosystems constitute the largest single North American shrub ecosystem and provide vital ecological, hydrological, biological, agricultural, and recreational ecosystem services. Disturbances have altered and reduced this ecosystem historically, but climate change may ultimately represent the greatest future risk to this ecosystem. Improved ways to quantify, monitor, and predict climate-driven gradual change in this ecosystem is vital to its future management. We examined the annual change of five sagebrush ecosystem fractional vegetation components from 1984 to 2011 in southwestern Wyoming derived from Landsat data using regression trees. Components included bare ground, herbaceousness, litter, sagebrush, and shrubs. Results show that bare ground displays an increasing trend in abundance, and herbaceousness, litter, shrub, and sagebrush show a decreasing trend in abundance. The magnitude and direction of component change was consistent with the downward trend in the historical amount of precipitation received, and components correlated to precipitation change with an average Pearson's correlation of 0.45.

We calculated future change predictions for each sagebrush component for the year 2050 by using pixels with a significant linear regression between historical component and precipitation patterns and inputting forecast precipitation amounts from

two IPCC scenarios, A1B and A2. Results show that bare ground was the only component that increased under both future scenarios, with the remaining four components decreasing under both future scenarios. These results successfully demonstrate the ability of long-term observations of sagebrush components in conjunction with corresponding precipitation change to infer empirical patterns of vegetation change without developing complex mechanistic models. This approach also provides the ability to use future component predictions to explore future climate impacts for specific applications. To demonstrate this, we applied 2050 forecast sagebrush components to contemporary (circa 2006) greater sage-grouse (Centrocercus *urophasianus*) habitat models to evaluate the effects of climate-induced habitat change. Under the two 2050 IPCC scenarios, predicted losses of ~12% of sage-grouse nesting habitat and ~4% of summer habitat from 2006 to 2050 would occur. These types of losses are especially significant when considering this rate of change is forecast in some of the most intact sagebrush habitats that remain (Bradley 2010), with much greater change likely on sage-grouse habitats in more peripheral ecosystem areas with greater susceptibility to climate change.

Because our results have demonstrated the successful ability of remote-sensingderived sagebrush ecosystem components to historically correlate with changing precipitation using simple linear models at the pixel level, we assume that results such as these can be generated over large areas using a wide variety of precipitation and model scenarios. Since each pixel has its own linear model, results would stay locally relevant even across large landscapes. Further, we postulate that more complex linear or nonlinear modeling could potentially offer improved results over our initial approach. This component approach offers products that are generic enough to support many specific applications but still achievable across large areas using existing remote sensing and climate data. This component-based prediction approach also offers a new capability to regionalize future precipitation patterns at a more local scale, quantifying results at a scale potentially useful to land managers. The ability to have a quick and low-cost approach to quantify future climate risk for local patches of habitat over large areas would prove invaluable to land managers who are often faced with the need to make rapid decisions without adequate information about future climate ramifications.

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CHAPTER 5

RESEARCH SUMMARY AND RECOMMENDATIONS

Research Hypotheses: Summary and Conclusions

The overall goal of this dissertation research was to define, develop, and test a large-area sagebrush ecosystem characterization, monitoring, and future prediction system based primarily upon remote sensing. This research was guided by four primary hypotheses which were designed to explore the accuracy at which sagebrush continuous field components can be characterized with remote sensing, the magnitudes of changes that can be detected annually and seasonally, the ability to forecast these changes into the future based on precipitation projections, and the magnitudes of sage grouse habitat change that can be expected with these future forecasts. Hypothesis conclusions are summarized below

Hypothesis 1). Characterization of sagebrush ecosystem components using remote sensing continuous field predictions can provide useful land management relevant information at improved mapping accuracies.

This hypothesis was confirmed. Results presented in Chapter 2 demonstrate the ability of regression trees (RT) to successfully parameterize the sagebrush landscape into components at three nested spatial resolution scales of imagery; 2.4-m, 30-m, and 56-m. (Homer et al, 2012). Component accuracies were independently validated. The root mean square error (RMSE) across all canopy components (excluding shrub height) averaged 6.32% for QB components, 8.66% for Landsat components, and 9.09% for AWiFS components. Validation results resulted in an average R^2 value across all components of 0.51 for QB, 0.26 for Landsat, and 0.15 for AWiFS, with all correlations significant at P <= 0.01. The four primary components (bare ground, herbaceous, shrub,

and litter) were also categorized into 10% intervals to analyze with a linear kappa to better understand error distribution within each category. These four components had a mean kappa value of 0.28. When comparing the independent accuracy assessment plots to LANDFIRE predictions (Rollins 2009), the sagebrush components outperformed LANDFIRE RMSE predictions, with a shrub value of 6.04% versus 12.64% for LANDFIRE, and a herbaceous value of 12.89% versus 14.63% for LANDFIRE.

The impact of this characterization research and the management utility of these developed products can be demonstrated using published literature citations reported to date from the resulting journal publication Homer et al, (2012). According to Google Scholar, as of October 7, 2013, this research has been formally cited 16 times since publication in 2012. Examples of direct applications of products in the state of Wyoming aimed at improving wildlife management include the development of statewide greater sage grouse seasonal models (Fedy et al, 2013 - in review), exploring disturbance factors influencing greater sage-grouse lek abandonment (Hess and Beck, 2012), understanding greater sage-grouse winter habitat (Dzialak et al., 2013b) and nesting habitat (Dzialak et al., 2013a). Examples of direct applications for improving research understanding include studying the effects of land cover and regional climate variations on long-term changes in sagebrush ecosystems (Xian et al., 2012a, Xian et al., 2012b), examining gradual ecosystem change using Landsat time series analyses (Vogelmann et al., 2012) and developing an improved approach to define nesting habitat for Gunnison sage grouse (Aldridge et al., 2012). Examples of in-direct applications for improving research understanding (i.e. research cited in support of a concept in a publication) cover a much

broader range of topics including monitoring of plant cover and soil erosion (Zeng et al., 2013), monitoring forests and rangelands using ecosystem performance anomalies (Rigge et al., 2013) and developing a biometric system for hand vein recognition (Trabelsi et al., 2013).

Hypothesis 2). The majority of annual and seasonal change observed in sagebrush ecosystem components through ground measurement can be replicated using remote sensing based continuous field component measurements.

This hypothesis was confirmed. Results presented in Chapter 3 demonstrate the utility of continuous field component predictions as a method capable of monitoring subtle change in a sagebrush ecosystem (Homer et al., 2013). Coincident ground and satellite measurements were completed over six seasons and four years. The values from seasonal and annual ground measurements were correlated with the corresponding satellite component measurements to test the ability of the component predictions to replicate ground measurements. Overall, annual predictions were more highly correlated than seasonal predictions, and QB had higher correlation values than Landsat. QB displayed a mean correlation value across all components of 0.85 for annual and 0.82 for seasonal. Landsat had a mean correlation value across all components of 0.77 for annual and 0.73 for seasonal. All QB and Landsat correlation values were significant at the .01 level.

The linear slope value was also calculated for each plot from annual ground and satellite measurements and then compared to test the ability of satellite component

predictions to replicate the direction of ground measured slope change. When all plots were pooled by component, QB had relatively high correlation values for each component (mean of 0.38 for all components) with all correlations significant. In contrast, Landsat had lower correlation values for each component (mean of 0.10 for all components), with a significant correlation value only for bare ground. However, when plots were pooled across all components and restricted to only ground measured plots that had both significant ANOVA and slope results (N = 14) an average correlation of 0.77 for QB and a correlation of 0.64 for Landsat was realized. This demonstrates the increased ability of this remote sensing approach to track change as the change on the ground becomes more significant.

Hypothesis 3). Annual and seasonal sagebrush ecosystem continuous field component change derived from remote sensing is significantly related to corresponding precipitation change

This hypothesis was confirmed. Results presented in both Chapters 3 and 4 demonstrate a significant relationship between changing sagebrush components and changing precipitation. In Chapter 3, (Homer et al., 2013) the correlation of six monthly and four annual DAYMET precipitation amounts to the corresponding monthly and annual component predictions were completed in southwest Wyoming. Of the 60 individual component and precipitation scenarios tested, 9 were significant at the 0.1 level. When correlation scenarios were averaged for single components, herbaceous had the highest mean correlation across all scenarios at 0.67, and shrub the lowest at 0.47.

The most significant individual correlation scenario was field measured herbaceous change against calendar year precipitation at -0.99.

In Chapter 4 (Homer et al., 2014) the annual change of five sagebrush components from 1984 to 2011 were also correlated to DAYMET annual precipitation amounts in southwest Wyoming. The magnitude and direction of component change was consistent with the downward trend in the historical amount of precipitation received, and study area wide summation of components correlated to precipitation change with an average Pearson's correlation of 0.45. All were significant at the 0.05 level. When tested at the single pixel level, about one quarter of each component pixels displayed a significant regression relationship (p> .90) between 28 years of component and precipitation change, further establishing the significant existing relationship between changing components and precipitation.

Hypothesis 4). Linear models developed from correlating historical responses of sagebrush ecosystem continuous field components to historical trends in precipitation variation can support quantification of feasible future sagebrush continuous field component and habitat change scenarios using future precipitation forecasts.

This hypothesis was confirmed. In Chapter 4, future change predictions were targeted for each sagebrush component pixel displaying a significant linear regression relationship (p>.90) between 28 years of historical component and precipitation change (Homer et al., 2014). Qualifying pixels amounted to about one fourth of the pixels for

each component available. Pixels with a non-significant relationship remained unchanged. Future change predictions for each sagebrush component for the year 2050 were then created using the regression relationship of qualifying pixels coupled with forecast precipitation amounts from two IPCC scenarios, A1B and A2. Bare ground increased under both future scenarios, with the remaining four components decreasing under both future scenarios. Specifically, under the A1B scenario bare ground had a net area increase of 48.98 km² with litter having a decrease of 49.82 km², sagebrush having a decrease of 45.74 km², shrub having a decrease of 44.83 km² and herbaceousness decreasing at 39.95 km². These results successfully demonstrate the ability of long-term observations of sagebrush components in conjunction with corresponding precipitation change, to support quantification of feasible future sagebrush continuous field predictions without developing complex mechanistic models.

Chapter 4 also documents the application of these 2050 future component predictions for inferring future sage grouse habitat change from a 2006 baseline (Homer et al., 2014). Under the two 2050 IPCC scenarios, predicted losses of ~12% of sage-grouse nesting habitat and ~4% of summer habitat from 2006 to 2050 could potentially occur. Results confirm the utility of future component predictions in developing habitat prediction scenarios.

Recommendations for Future Research

The research reported in this dissertation has successfully achieved the research goal of defining, developing, testing and demonstrating a sagebrush ecosystem characterization, monitoring, and future prediction system based primarily upon remote sensing. There remain many areas for future research that could expand upon initial results presented here. Areas that would likely be most beneficial are described by category below.

Test characterization improvement with new remote sensing sensors

Since the completion of this research, new sensors are available which could improve the characterization capability and accuracy reported here. For moderate resolution imagery, the successful launch of Landsat 8 provides new remote sensing capability (Irons et al., 2012). The increased dynamic range of the sensor to 12 bit provides new ability to more finely characterize the spectral signal into meaningful information. Also, the signal-to-noise ratio has been improved, which should allow for improved discrimination potential. Landsat 8 has not only added three additional spectral bands over Landsat 5, but remaining bands have been narrowed and fine-tuned, potentially enhancing discrimination capability in the sagebrush ecosystem. The upcoming launch of the European Sentinel-2 mission also deserves careful testing since it offers capabilities consistent with Landsat, but will double potential observation frequency.

New high-resolution sensors are also available. For example, the launch of the WorldView-2 satellite in 2009, offers 8 bands of multispectral imagery at 1.84 m spatial resolution. The addition of a narrow red edge band (705 - 745 nm) to this sensor

strategically targeted between visible red and the near infrared for sensitive vegetation detection seems especially promising (Immitzer et al., 2012). Initial sagebrush characterization research in Idaho with WorldView-2 has shown about a 10% improvement in component accuracy (Homer 2013, unpublished research). Because the sagebrush ecosystem is already a difficult remote sensing characterization environment, the new remote sensing capabilities of sensors like Landsat 8 and WorldView-2 should be especially useful for improving characterization capability and accuracy and should be explored.

Further optimize ground plot collection

The modeling method used to characterize the extent and spatial distribution of sagebrush components over large areas requires considerable amounts of ground training data and high resolution imagery to be effective (Homer et al., 2012). Ideally ground training data are derived from good quality field measurements collected during appropriate seasons and coincident with high-resolution remote sensing data (Homer et al., 2012). Although this method has proven its utility, the need to develop these products across even larger areas (Xian et al., 2013) will require further optimizing of ground and high resolution data collection to ensure adequate products can be developed for the lowest cost possible. Both stages of this process need further exploration, including analysis of the optimal ratio of ground plots for high resolution imagery

characterization, and the optimal ratio of high resolution image characterization locations to parameterize the moderate resolution Landsat imagery (Xian et al., 2012c).

Produce longer-term coincident ground and sensor measurements

Research represented in Chapter 3 has demonstrated the need for seasonal and annual coincident ground and satellite measurements to truly understand the change relationship between ground and sensors (Homer et al., 2013). Initial results demonstrated that as the magnitude of change measured on the ground increased, the effectiveness of the remote sensing components in tracking that change also increased. Further research that explores these results in more depth by extending the initial sample size across both time and space would be valuable. Results would provide key feedback for further determining the significant detectable change thresholds for different types of change and sensors, and would greatly contribute to more effective monitoring (Washington-Allen et al., 2006).

Explore the utility of more complex linear or nonlinear models to better capture the relationship between component change and precipitation change to improve future component predictions

Research results presented in Chapter 4 demonstrate that a significant relationship exists between component change and precipitation change over time (Homer et al., 2014). This relationship was developed using a simple linear model across 28 years. However, because this is a very dynamic semi-arid system with erratic precipitation, it may be that a more sophisticated modeling approach is warranted to capture these complex patterns (Schlaepfer et al., 2012, Tietjen et al., 2010, Kamarianakis et al., 2006) A variety of more complex linear or non-linear model approaches could possibly offer a more significant relationship between components and precipitation (Weltzin et al., 2003), and ultimately produce a more accurate overall model approach for prediction. Hence, research that explores new modeling options would likely provide substantial benefit.

Expand future precipitation scenario testing across larger landscapes with new scenarios

The research represented in Chapters 3 & 4 exploring the relationship between component change and precipitation change was completed on relatively small areas. These areas are adequate to explore diverse sagebrush component response, but relatively small for exploring more complex precipitation response at the 1 km scale precipitation data are available. Improvement in downscaling of both historical and future precipitation predictions is still evolving (Daly 2006), and spatial scale mismatch between climate data and remote sensing is a vulnerability of this approach. Applying this research over a larger spatial area encompassing more complex precipitation response patterns, would likely enable deeper understanding of the relationship between component change and precipitation change. This would not only improve monitoring understanding, but would ultimately improve component forecast modeling.

The research presented in Chapter 4 also demonstrated how the application of future precipitation scenarios from two IPCC scenarios (A1B and A2) and one model (NCAR-CCSM3.0 model) could be projected into future component scenarios. However, there exists many more future precipitation models with various strengths and weaknesses which should be further examined and tested to find the most reliable model for representing the conditions of the sagebrush ecosystem (Schlaepfer et al., 2012). Once a model is selected, various future scenarios could then be better explored, and scenarios developed with a potentially higher confidence in results.

Explore relevancy of components to a greater variety of applications

Research results presented in Chapter 4, demonstrate the utility of sagebrush components to a sage grouse habitat application. This component approach was designed to offer a more objective, improved way to characterize and monitor ecosystem change over larger areas than traditional methods have allowed (Homer et al., 2012). The component approach was also specifically designed to offer generic component building blocks potentially useful in a wide variety of applications. Chapter 4 demonstrates one successful application of this assumption for wildlife habitat; however this assumption needs to be further tested across broader applications beyond wildlife habitat. There are many other potential applications of current interest in the sagebrush ecosystem where remote sensing components could provide valuable insight. Additional application examples include vegetation change patterns and implications that cover grazing (Davies et al., 2010), invasive species (Reisner et al., 2013), fire recovery (Davies et al., 2012) and energy extraction (Walston et al., 2009).

Test the climate forecasting approach in a more climatic vulnerable part of the sagebrush ecosystem

The maximum extent of the research presented in this dissertation encompassed the state of Wyoming (Chapter 2), with subsequent chapters focused on much smaller areas in Southwest Wyoming (Chapter 3 & 4). These are all areas within the core climate range of the sagebrush ecosystem (Knick et al., 2003; Bradley 2010). Chapter 4 research results on sagebrush component forecasting in Southwest Wyoming, would be especially beneficial to extend to a different part of the ecosystem. Additional research exploring the same approach in a more climatic vulnerable peripheral sagebrush area in the west would be warranted. Research would not only provide possible insights on rates of change in another part of the ecosystem, but provide additional insights into the robustness of the method.

Test the robustness of the methods in other semiarid ecosystems

This research has been entirely focused on the sagebrush ecosystem. However, remote sensing characterization of semiarid shrub lands in general is still lacking (Booth and Tueller, 2003; West, 2003), with monitoring and forecasting applications in these systems also likely to benefit from a component-based approach (Homer et al., 2012). Testing this approach in other ecosystems would not only provide important insight into the robustness of this approach in other ecosystems, but potentially advance remote sensing characterization and monitoring in semi-arid systems in general (Xian et al., 2013).

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