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Forecasting sagebrush ecosystem components and greater sage-grouse habitat for 2050: Learning from past climate patterns and Landsat imagery to predict the future

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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 precipitation (daily gridded climate data) and five remote sensing ecosystem sagebrush vegetation and soil components (bare ground, herbaceous, litter, sagebrush, and shrub) from 1984 to 2011 in southwestern Wyoming. Bare ground displayed an increasing trend in abundance over time, and herbaceous, litter, shrub, and sagebrush showed a decreasing trend. Total precipitation amounts show a downward trend during the same period. We established statistically significant correlations between each sagebrush component and historical precipitation records using a simple least squares linear regression. Using the historical relationship between sagebrush component abundance and precipitation in a linear model, we forecasted the abundance of the sagebrush 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 km^2 (0.9%) under the A2 scenario. The remaining components decreased under both future scenarios: litter had the highest net reductions with 49.82 km^2 (4.1%) under A1B and 50.8 km^2 (4.2%) under A2, and herbaceous had the smallest net reductions with 39.95 km^2 (3.8%) under A1B and 40.59 km^2 (3.3%) under A2. We applied the 2050 forecast sagebrush 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 remote sensing based sagebrush components, when coupled with precipitation, to forecast future component response using IPCC precipitation scenarios. Our approach also enables future quantification of greater sage-grouse habitat under different precipitation scenarios, and provides additional capability to identify regional precipitation influence on sagebrush component response.

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1. 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 sagebrush-obligate species. For example, ecosystem decline has severely affected greater sage-grouse (*Centrocercus urophasianus*; hereafter 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).

In addition to 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,b). 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, 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 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 scenarios can provide critical information to manage these lands. Specifically, information about long-term variations of sagebrush ecosystem components can determine the potential relationship between magnitudes of component change and the regional climate by using information about long-term spatiotemporal variations in sagebrush ecosystem components.

Remote sensing images interpreted into fractional vegetation and soil 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,b; Homer et al., 2013). This process can draw on the Landsat (LS) 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-m resolution of LS 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 relatively high resolution remotely sensed information, a common challenge is the difference in spatial resolution of remotely sensed products compared to climate data. In order to make an effective comparison, rescaling of climate data to better match the higher resolution remote sensing products is necessary. This rescaling (called downscaling) of climate information such as precipitation data can provide for finer scale analysis of smaller regions (Hijmans et al., 2005; Wang et al., 2012). For historical precipitation, having the longer temporal records available in finer spatial scale products provides additional 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 opportunity to explore regional scale links of climate change to observed ecosystem change. Linear regression analysis is one approach that has been widely used to link climate data to remote sensing derived vegetation condition for large area biomass and crop yield predictions (Quarmby et al., 1993; Prasad et al., 2007).

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 Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report 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 too 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 techniques can vary in accuracy and output resolution. Because shifts in precipitation may have a greater impact on ecosystem dynamics than rising CO_2 or temperature (Weltzin et al., 2003), downscaled GCMs that accommodate regional processes (e.g., land-water interactions and topography) are key when predicting future 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 associated effects 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. Quantitative monitoring of habitat trends has been identified as a key requirement to understand and reduce uncertainty about climate change impacts on habitat and associated wildlife species (U.S. Fish and Wildlife Service, 2013). Development of future habitat scenarios for sage-grouse could allow for application to other species of conservation concern. Seasonal habitat models have been developed for sage-grouse across the state of Wyoming (Fedy et al., 2014) using sagebrush components as base habitat layers (see Homer et al., 2012). This provides an ideal opportunity to evaluate how climate-induced changes in projected future habitat conditions will affect sage-grouse populations.

We theorized that developments in capturing gradual change across time using remote sensing sagebrush components and the downscaling of precipitation could be combined to correlate precipitation trends with component abundance across 28 years. We further theorized that these precipitation trends would influence

sagebrush component distribution and pattern, and this influence could be quantified into potential future component scenarios and the subsequent effect on sage-grouse habitat. 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 applied these models to 2050 IPCC precipitation projections to forecast changes in components though to 2050, based on the 28-year slope relationships. Third, we used predicted 2050 sagebrush components to reapply sage-grouse habitat models to understand how sage-grouse habitat quality and quantity might change as a result of precipitation induced changes in sagebrush components.

2. Data and methods

2.1. Overview

We examined the annual change of five sagebrush ecosystem components (hereafter called components) from 1984 to 2011. We characterized bare ground, herbaceous (herbaceousness), litter, sagebrush, and shrub cover as continuous fields in one percent intervals. We used 2006 and 2007 QuickBird (QB) satellite data with coincident field measurements to train 2006 LS satellite data to create a 2006 base analysis year. We then normalized historical LS imagery every year back to 1984, with comparison to the 2006 base to find areas that had changed spectrally (Table 1). 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 period was downscaled to a 30 m grid, and regression analysis 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 (Table 1). We explain each methodological step by section below.

2.2. Study area

Our study area is located in southwestern Wyoming, United States (Fig. 1), and occupies 8330 km^2. It contains a range of topography with elevations from 1865 to 2651 m, and slopes up to 48°. 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 meadows where a high sub-surface water table in the sandy areas creates higher 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 elevations of the 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, with most areas 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; see Fig. 1). Site 1 is the location where comprehensive trend analysis research has been on-going for many years (Homer et al., 2013).

2.3. Baseline data collection

Several key steps were required to calculate component measurements for the base year (2006) and additional years between 1984 and 2011 including: (1) collect and pre-process LS data for all years; (2) calculate vegetation continuous field components for the base year (2006); (3) normalize spectral reflectance of all scenes to the base year (2006); (4) compare yearly LS 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. Each of these steps is described in detail below.

2.3.1. Image collection and pre-processing

We acquired eight QB images (64 km^2 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 2×2 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 from 1984 to 2011 for path 37/row 31 and processed using the automated Landsat Product Generation System (LPGS). We selected LS products because they 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 and Homer, 2010).

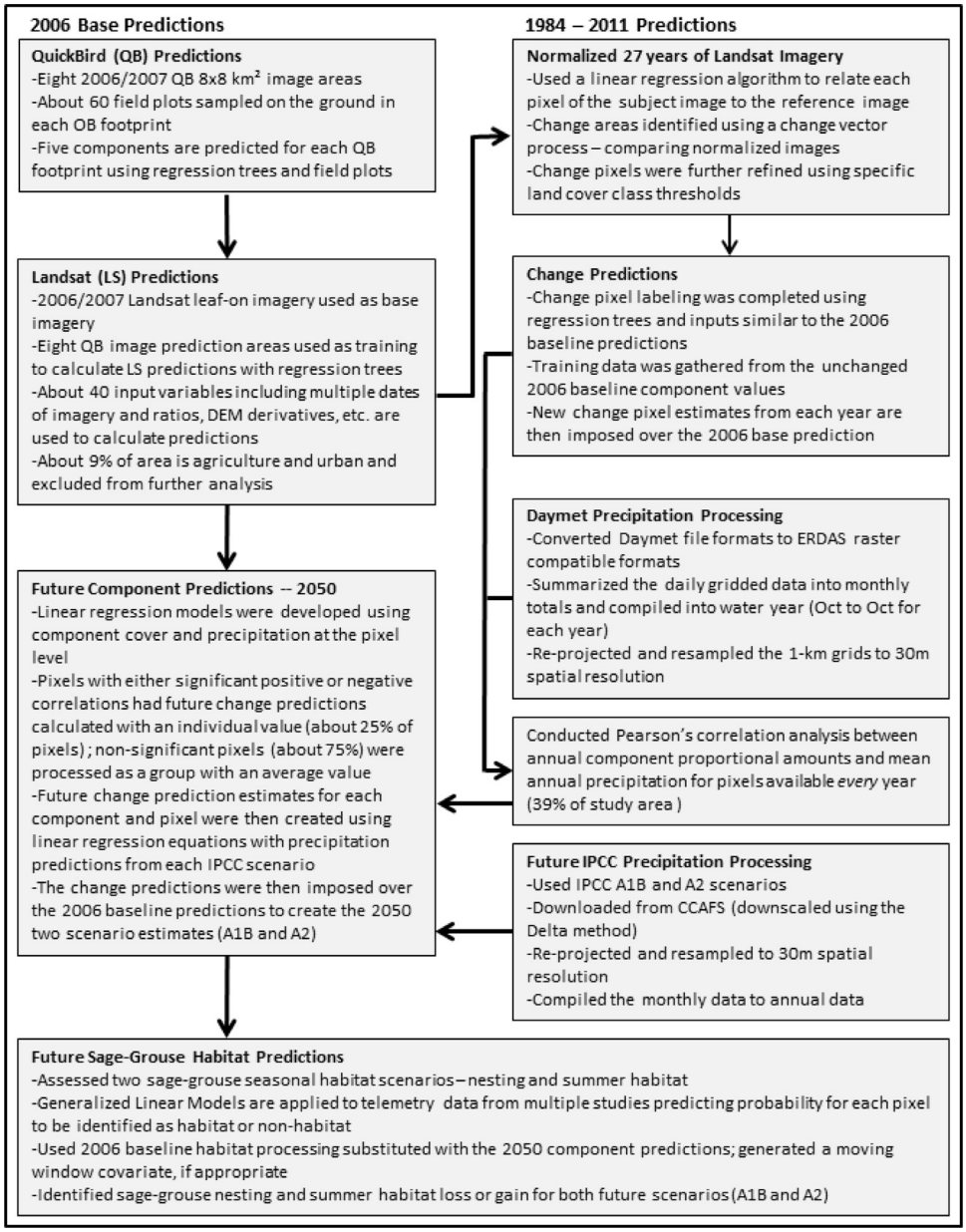
2.3.2. Component base year predictions

We produced the spatial distributions of five sagebrush components (bare ground, herbaceous, 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 models (cross validation correlations across all components averaged a correlation of 0.86) to produce component estimates (training protocols and accuracies are described in Homer et al. (2012, 2013)). In order to ensure a rigorous training sample at the LS scale, QB predictions 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 a larger ecosystem scale classification application. LS base predictions were modeled using three seasons of imagery, coupled with a Digital Elevation Model (DEM) and ancillary data (Homer et al., 2012); model cross validation correlations across all components averaged a correlation of 0.92.

2.3.3. Image normalization, change identification, and prediction

Normalizing the spectral reflectance of the LS 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 using vegetation specific thresholds to identify change (Xian et al., 2012b). 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. 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

Table 1
Flow diagram of all major methodological steps required to characterize sagebrush components, quantify change across years, relate change to changing precipitation and forecast future component and Sage grouse habitat predictions.



in the histogram to ensure the RT had adequate training for the full range of each component and good representation of extreme component values. 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 per-pixel 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 being 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. The correlation of annual component proportions and annual water year mean values were calculated 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 et al., 1997). 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

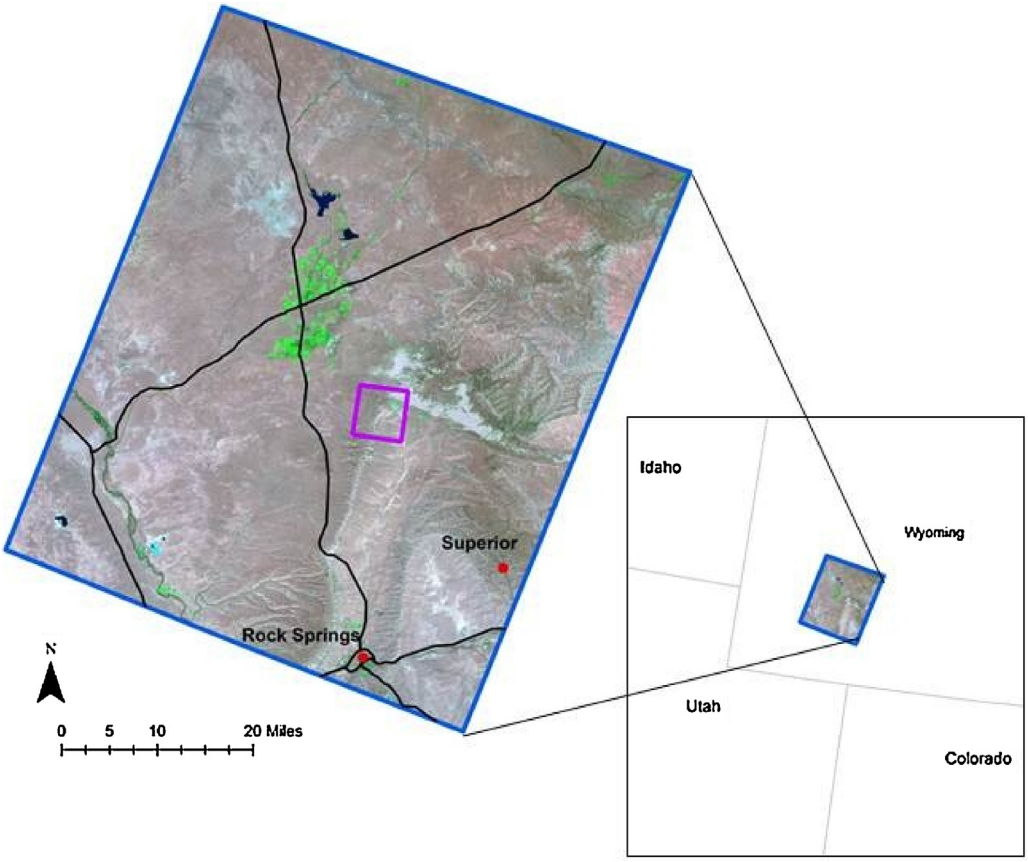


Fig. 1. Study area extent, located north of Rock Spring, WY, U.S.A. The small magenta rectangle in the center of the study area is the location of site 1, where intensive monitoring work has been ongoing since 2006 (see Homer et al., 2013).

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 with 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 × 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–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 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″ 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 into monthly precipitation, which was then 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 climate predictor that best predicted sagebrush cover component change (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

Previous field experiments conducted in the northern Great Basin using rain shelters for different precipitation treatments suggested that the fractional cover of most sagebrush components have a significant linear response to annual precipitation (Bates et al., 2006). In our research, we conducted exploratory

Table 2
Nesting and summer habitat logistic regression model coefficients and standard errors (in parentheses) used to predict effects of changes in sagebrush habitat components due to climate change in 2050. Many variables were included in the original models (see Fedy et al., 2014). These were also applied to future scenarios analyses developed here; however, only the sagebrush habitat components within those models were changed and are shown here.

Sage-grouse	Nesting habitat		Summer habitat	
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.

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. Because the fractional cover of sagebrush components and annual (water year) precipitation had the highest correlation, this component was selected for further development. 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):

$$Y = a + bX \quad (1)$$

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: $0.05 < p \leq 0.1$, $0.01 < p \leq 0.05$, and $p \leq 0.01$ and selected $0.05 < p \leq 0.1$ as the significance threshold. Only pixels that had significant positive or negative correlations were retained for calculating the future change prediction at the 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. Although the linear model is simple, easily developed, and presented a reasonable starting point, there are limitations with using this approach. A linear model may not adequately represent physical processes of sagebrush components responding to climate variations.

2.6.2. Future change prediction

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

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

where i and j represent pixel locations, $Y_{i,j}(k, 2050)$ represents the fractional cover of the sagebrush component k for a pixel located at i and j, $b_{i,j}(k)$ is a slope for the component k, $X_{i,j}(2050)$ is the annual precipitation for 2050, and $X_{i,j}(2006)$ is the annual precipitation for 2006. The 2050 annual precipitation prediction serves as the independent variable in Eq. (2) to project the fractional cover of the five sagebrush components to 2050. For pixels that have non-significant correlations (negative for bare ground and positive for other components), a mean slope for the entire study area (all pixels) is used to replace $b_{i,j}(k)$ in Eq. (2), for that specific component. Since future precipitation change may not follow the exact same patterns in areas that experience significant correlations, the use of mean slope for non-significant pixels allows impacts of more extreme future precipitation values over non-significant areas to 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 were recently developed for the state of Wyoming (Fedy et al., 2014). 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 (30 m) on the landscape, and this continuous surface was subsequently thresholded into a binary surface depicting habitat and non-habitat for sage-grouse; see Fedy et al. (2014) for details. Vegetation layers evaluated for sage-grouse habitat selection 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 change. Fedy et al. (2014) developed models for nesting, late-summer, and winter, using different spatial extent

Table 3
Total annual percent proportional cover change compiled as a total study area value, by component. This metric was calculated using only valid pixel values cloud free 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 (3288 km^2).

Year	Components – percent coverage				
	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%

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., 2014).

In the original statewide sagebrush component products, edge matching in LS overlap zones and standardization was required to stitch together models developed for individual LS scenes (Homer et al., 2012). Our target study area was partially within the overlap zone of LS 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 LS 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., 2014), we took the new pixel estimates for the 2006 base year generated from the single LS 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 in the original base you (2006). We applied the thresholding values used in the original models to develop a binary habitat/non-habitat base map. Original habitat models were developed at two scales (patch and landscape; see Fedy et al., 2014), and coefficients for all sagebrush habitat components contained within the original GLM logistic regression RSF model responses are shown in Table 2. 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 covariates where necessary, allowing us to generate habitat prediction maps for 2050.

3. Results

3.1. Historical component and precipitation change and correlation

We measured annual change in five sagebrush components (bare ground, herbaceous, 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 (3288 km^2) cloud free in all years. 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%, herbaceous at 13.56%, shrub at 11.21%, and sagebrush at 9.4% (Table 3). 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 3). 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 in each year over the entire study area from Daymet observations. Precipitation varied from a low of 125 mm in 2001 to a high of 404 mm in 1986 (Fig. 2a). Overall, there is a downward trend in the

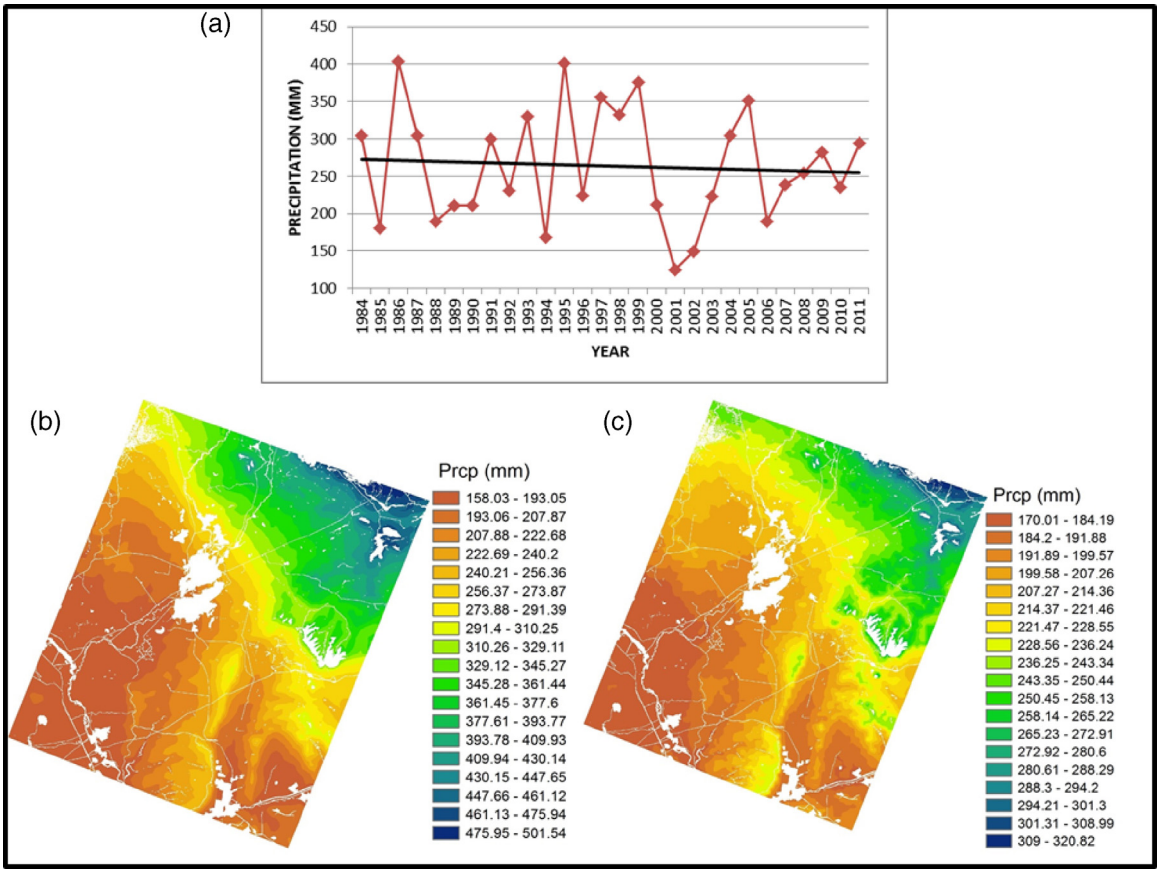


Fig. 2. Mean annual precipitation from 1984 to 2011 over the study area calculated from Daymet data by water year with the linear trend line (a), the average annual precipitation between 1984 and 2011 (b), and mean annual precipitation predicted from NCAR-CCSM3.0 under the A2 scenario for the year 2050 (c). The linear regression equation of mean annual precipitation displayed in (a) is expressed as $y = -0.8761x + 275.71$ in which x is the time and y is annual precipitation, with $r^2 = 0.01$. The white in (b) and (c) represent the areas without sagebrush cover.

historical amount of precipitation received (Fig. 2a). Fig. 2b shows the 1984–2011 mean annual Daymet precipitation for the study area and Fig. 2c shows mean annual precipitation for the year 2050. The precipitation is somewhat greater in the northeast part of the area than in the southwest. Pearson's correlations between component study area means and annual precipitation study area means ranged from 0.56 for herbaceous, to 0.48 for sagebrush, 0.43 for shrub, 0.42 for litter, and 0.38 for bare ground. Herbaceous and sagebrush correlation values were significant at the 0.01 level, and all others significant at the 0.05 level.

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% (7580 km^2) 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 4). 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 individual pixels qualifying for future updating at 22.3%, and litter had the highest proportion of individual pixels qualifying for future updating at 24.6% (Table 4).

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 see Table 5). The NCAR-CCSM3.0 model presented the most divergent precipitation

Table 4
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. Pixels with significant correlations had individual linear models developed to forecast each component, while pixels with non-significant correlations required a mean slope value from the entire study area.

Component	% pixels with significant positive correlation	% pixels with significant negative correlation	% pixels with both positive and negative correlations	% pixels with no significant correlations
Bare ground	6.1	18.3	24.4	75.6
Herbaceous	12.8	9.5	22.3	77.7
Litter	18.8	5.8	24.6	75.4
Sagebrush	18.6	5.9	24.5	75.5
Shrub	17.4	6.7	24.1	75.9

Table 5
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 to 2011 was 263 mm.

Model	2050 scenario	
	A1B (mm)	A2 (mm)
NCAR-CCSM3.0	228	216
GFDL-CM2.1	236	230
UKMO-HADCM3	228	229

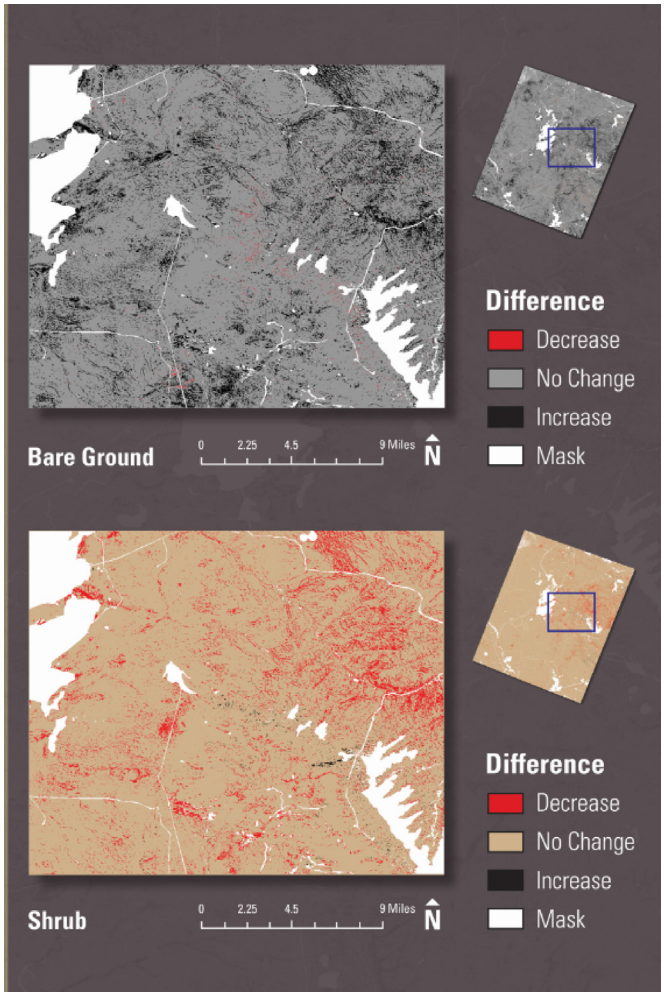


Fig. 3. Spatial distrubution of bare ground and shrub component prediction change between 2006 and 2050 for the A1B scenario across the entire study area. Component reductions are represented in red and orange tones and increases in green tones.

amounts between A1B and A2 (Table 5) and was selected for linear modeling implementation. The annual precipitation in 2050 predicted by NCAR-CCSM3.0 under the A2 scenario is represented in Fig. 2c. This prediction captures a similar spatial distribution

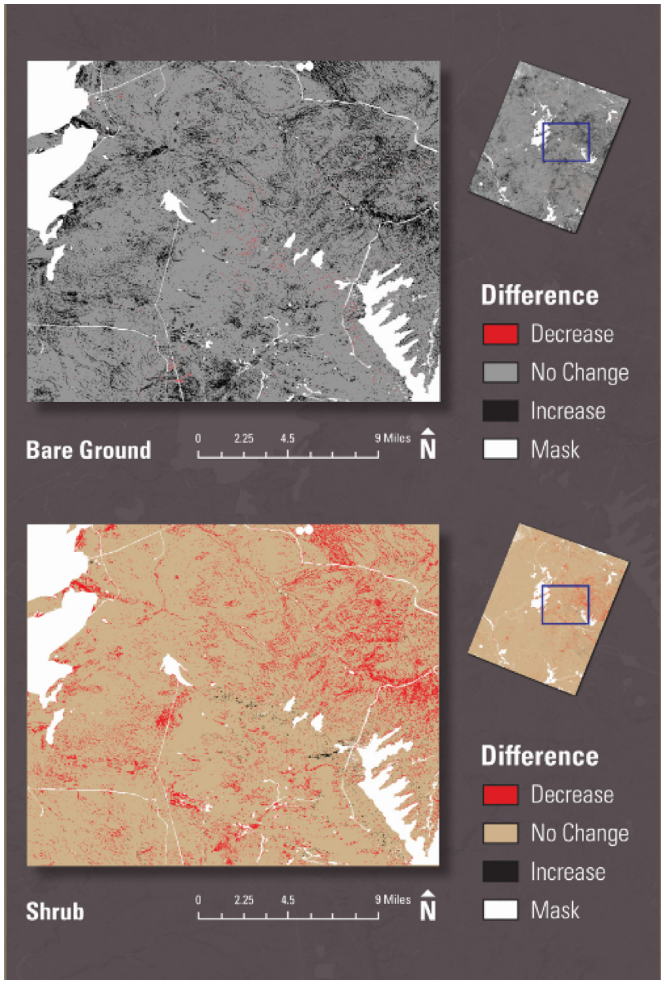


Fig. 4. Spatial distrubtion of bare ground and shrub component prediction change between 2006 and 2050 for the A2 scenario across the entire study area. Component reductions are represented in red and orange tones and increases in green tones.

pattern to the historical pattern although the magnitude is smaller in many areas. When forecast precipitation amounts from IPCC scenarios were input into equations and component surfaces calculated in 2050, bare ground was the only component that increased under both future scenarios. Bare ground had a net increase of 48.98 km^2 (1.1%) across the study area under the A1B scenario and a net increase of 41.15 km^2 (0.9%) under the A2 scenario (Table 6, Figs. 3 and 4). The remaining components decreased under both future scenarios, with litter having the highest net reductions under both scenarios (A1B scenario at 49.82 km^2 (4.1%), and the A2 scenario at 50.8 km^2 (4.2%)), and herbaceous the smallest net reductions under both scenarios (A1B scenario at 39.95 km^2 (3.8%), and the A2 scenario at 40.59 km^2 (3.3%)) (Table 6, Figs. 3 and 4).

Table 6
Positive and negative total component change amounts in km^2 for 2050 IPCC A1B and A2 scenario forecast change results compared to the 2006 component base predictions.

Component	A1B scenario			A2 scenario		
	− change (km^2)	+ change (km^2)	Net change (km^2)	− change (km^2)	+ change (km^2)	Net change (km^2)
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

Table 7
Total amount of study area that contained sage-grouse nesting and summer habitat in the 2006 base year and in 2050 using sagebrush 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)	3059.876	2704.859	2699.100	1668.902	1602.087	1601.553
Habitat gain (km^2)	–	0.077	0.124	–	0.644	0.713
Habitat loss (km^2)	–	355.093	360.900	–	67.460	68.063

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 3059 km^2, or roughly 37% of the sage-grouse study area where we had data available (Table 7), and summer habitat covered roughly 21% of the sage-grouse study area (~1669 km^2; see Table 7). For nesting habitat, the 2050 model for IPCC A1B habitat estimates applied to the sage-grouse model predicted a loss of 355 km^2 of adequate sage-grouse habitat, resulting in an 11.6% loss from habitat identified in 2006, and the IPCC A2 had a loss of ~361 km^2 of sage-grouse habitat, or 11.8% (Table 7, Fig. 5). For summer habitat, the 2050 model for IPCC A1B scenarios predicted a loss of ~67.5 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 7, Fig. 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 km^2

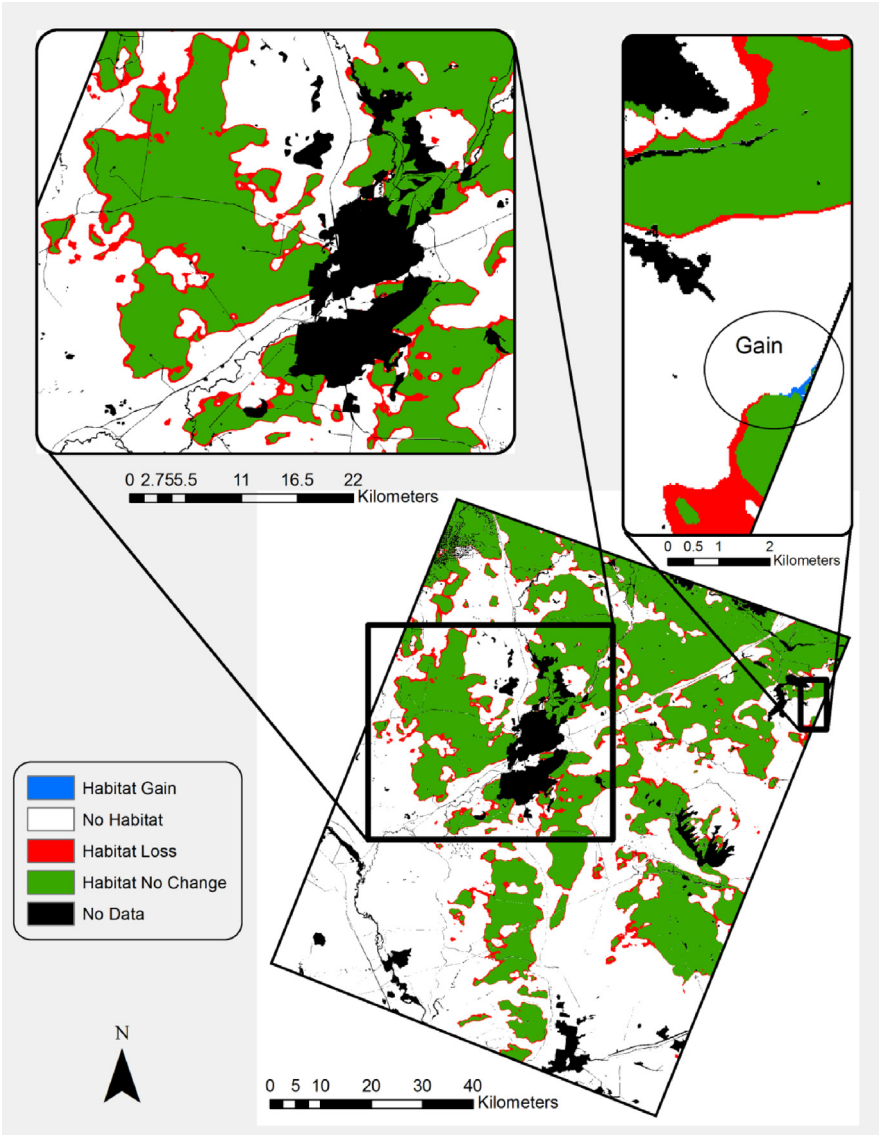


Fig. 5. Predicted changes in sage-grouse nesting habitat from 2006 to 2050 from climate scenerio A1B. Changes are based on the original sage-grouse habitat models from Fedy et al. (2014) for the 2006 base year, which were then predicted to 2050 based on changes in sagebrush vegetation characteristics linked to the A1B 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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

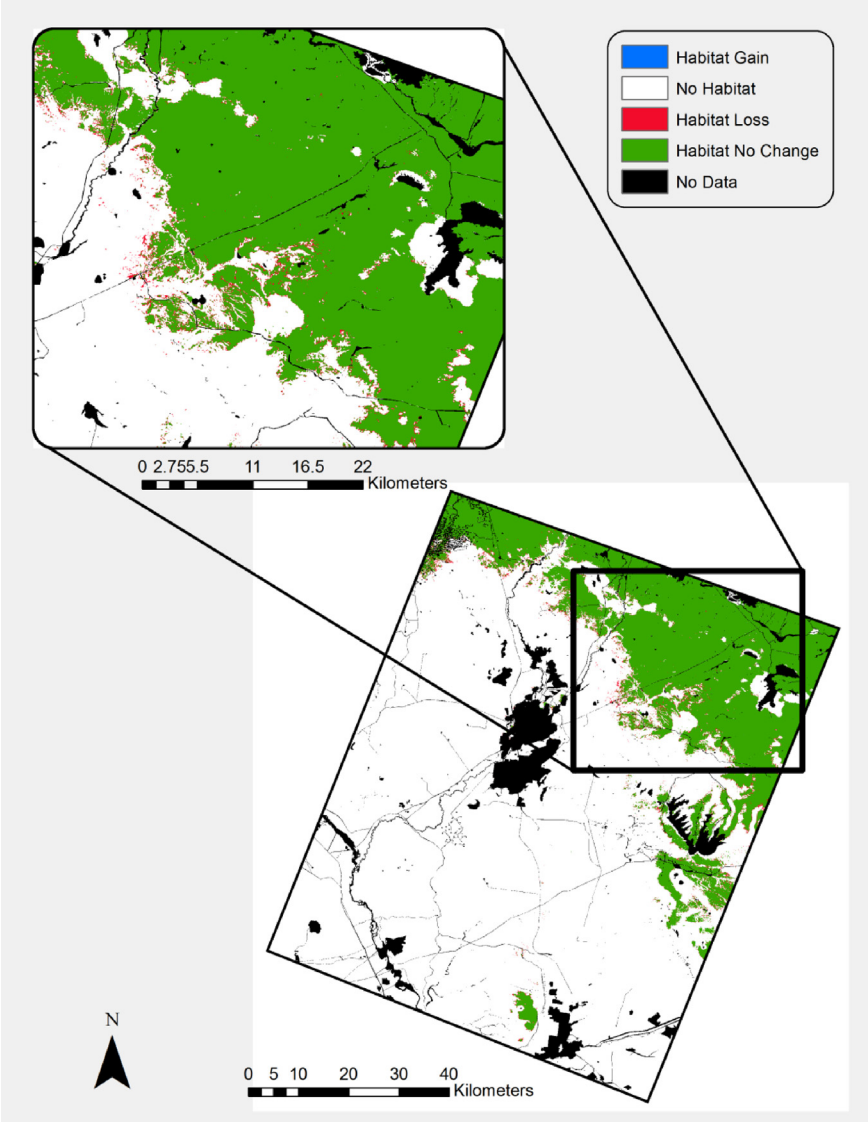


Fig. 6. Predicted changes in sage-grouse summer habitat from 2006 to 2050 from climate scenerio A1B. Changes are based on the original sage-grouse habitat models from Fedy et al. (2014) for the 2006 base year, which were then predicted to 2050 based on changes in sagebrush vegetation characteristics linked to the A1B 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. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

in all cases (Table 7). Habitat losses can be seen in Figs. 5 and 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 1500 m radius window.

4. 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 are suffering from other habitat degradation forces, a potential additional 11% loss of future habitat from climate change could be very detrimental to some 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, LS 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 2nd (45 days), and 1986 had the latest capture difference from the base at August 27th (39 days). Component trends can be seasonally influenced, especially the more ephemeral components of bare ground, herbaceousness, and litter (Homer et al., 2013). Our LS 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. We also note that image change analysis can contain certain biases due to the qualities of satellite imagery and the limitations of the change detection method. According to previous results from change analysis and change validation using two decades of images, the overall accuracy for shrub vegetation change was about 89% (Xian et al., 2009). The method used in this analysis is similar and we anticipate that approximately the same uncertainty could exist.

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,b; 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 3), 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 LS 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 herbaceous 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 the focus of 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 herbaceous 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 model forecasting.

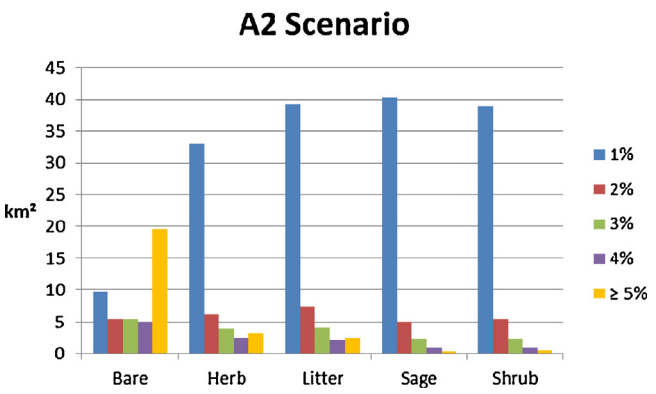


Fig. 7. The amount and distribution of change magnitudes between current and future predictions at the pixel level, summed across the study area by component for the A2 scenario. This demonstrates that most future single pixel component predictions were mostly changing by only 1–2%.

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; see Fig. 2a). 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 on our type of study area terrain is potentially 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 modeled.

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 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 for these areas. This ensures model predictions capture the impact of extreme patterns of future precipitation on sagebrush components without introducing unnecessary arbitrary changes. It is necessary to point out that future sagebrush component predictions are based on a statistical model created from linear regression analysis of historical trends of climate data and sagebrush cover. The linear correlation does not completely represent physical processes that determine the growth or decline of sagebrush ecosystem components. Also, a linear trend usually denotes an average status and can miss true variation associated with climate perturbations. However, it does represent a reasonable initial starting point for our analysis.

The total 2050 predicted component mean study area change is relatively modest for both IPCC scenarios (Table 6). 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 had a different prediction for 2050 (Table 4), with most changing by relatively small increments of 1–2% from the 2006-based prediction (Fig. 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 linear slopes resulting in change amounts greater than 1%. These pixels were typically distributed in 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.

Our approach of developing remote sensing components across 28 years using the historical LS 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, with potential biases from data simulated by GCM's discussed in previous studies (Watanabe et al., 2012). To avoid biases in the GCM simulations, a simple bias correction was implemented to both temperature and precipitation when these data were downscaled by CCAFS. 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,c; 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 sage-grouse have not been fully evaluated. 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 3059 km^2 and 1669 km^2 of our 7580 km^2 study area would be suitable sage-grouse habitat for nesting, and summer, respectively (Table 7). Our habitat models predicted that 45 km^2 of this area would experience decreases in sagebrush cover, and herbaceous cover could also decline in ~40 km^2 of habitat, using either climate scenario (Table 7). Given sage-grouse in our study area (Fedy et al., 2014) and across their range select for areas of increased sagebrush cover (Aldridge and Boyce, 2007; Aldridge et al., 2008; Doherty et al., 2010; Aldridge and Boyce, 2008) and also select for increased herbaceous cover (Crawford et al., 2004; Aldridge et al., 2008; Fedy et al., 2014), 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 7, Figs. 5 and 6) due to climate alone are substantial. 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 populations in more fringe habitats.

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., 2003; 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., 2014). 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. 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 vegetation and soil components from 1984 to 2011 in southwestern Wyoming derived from LS data using regression trees. Components included bare ground, herbaceous, litter, sagebrush, and shrubs. Results show that bare ground displays an increasing trend in abundance, and herbaceous, 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 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 the predicted rate of change is based on data from an intact and robust sagebrush system (Bradley, 2010). This system likely has increased resilience to some effects of climate change. It is reasonable to expect that less intact and more peripheral sagebrush habitats will be less resilient to change and thus, sage-grouse habitat in these areas could be more susceptible to climate change.

Because our results have demonstrated the successful ability of remote-sensing-derived 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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