**Characterization of shrubland ecosystem components as continuous fields in the northwest
United States**

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Abstract

Accurate and consistent estimates of shrubland ecosystem components are crucial to a better understanding of ecosystem conditions in arid and semiarid lands. An innovative approach was developed by integrating multiple sources of information to quantify shrubland components as continuous field products within the National Land Cover Database (NLCD). The approach consists of several procedures including field sample collections, high-resolution mapping of shrubland components using WorldView-2 imagery and regression tree models, Landsat 8 radiometric balancing and phenological mosaicking, medium resolution estimates of shrubland components following different climate zones using Landsat 8 phenological mosaics and regression tree models, and product validation. Fractional cover of nine shrubland components were estimated: annual herbaceous, bare ground, big sagebrush, herbaceous, litter, sagebrush, shrub, sagebrush height, and shrub height. Our study area included the footprint of six Landsat 8 scenes in the northwestern United States. Results show that most components have relatively significant correlations with validation data, have small normalized root mean square errors, and correspond well with expected ecological gradients. While some uncertainties remain with height estimates, the model formulated in this study provides a cross-validated, unbiased, and cost effective approach to quantify shrubland components at a regional scale and advances knowledge of horizontal and vertical variability of these components.

1. Introduction

Shrubland ecosystems cover a large portion of the global land surface, mostly in semiarid ecosystems. For example, several global land cover datasets have estimated that shrub cover occupies about 14% (Loveland et al., 2000; Broxton et al., 2014) to 17% (Hansen et al., 2000) of the global land. Shrub cover was consistently estimated as 21% of total land across the conterminous United States in 2001 and 2006 (Fry et al., 2011). Shrubland ecosystems are critical for determining regional biodiversity, global biogeochemical cycles, and energy and gas fluxes (Wallace et al., 2003; Schwinning et al., 2005; Hamada et al., 2013). Shrublands provide many ecosystem services to human populations around the world (Sant et al., 2014). Overall, shrub and grass cover about 2.9 million km², or 36% of the total land in the conterminous United States (Fry et al., 2011). In western North America, shrubland and grassland comprise the largest rangeland vegetation biomes. Sagebrush (*Artemisia* spp.) communities alone are estimated to cover 0.23 million (Branson et al., 1967) to 0.25 million km² (West, 1983) in the western United States. The sagebrush area is about 13.3 to 14.5% of the total shrubland in the conterminous United States.

Many recent changes, including diminishing vegetation cover, encroachment of woody and invasive species, and the degradation of shrub and grass communities in general, have been observed in arid and semiarid ecosystems throughout the Western United States where much of the country's shrubland community occurs (Connelly et al., 2004; Schroeder et al., 2004; Bradley et al., 2006; Homer et al., 2009; Homer et al., 2012; Xian et al., 2012a). For example, the most dominant shrub community in the Western United States, sagebrush, has suffered steadily declining quality and quantity from the historical distribution. In recent decades, the speed of the deterioration has accelerated due to the effects and interactions among land use change, livestock grazing, fire, invasive species, and climate change (Berlow et al., 2002; Davies et al., 2007; Olsoy et al., 2014). Recent natural gas extraction in western Wyoming has further significantly affected sagebrush communities in the region by reducing and degrading sagebrush habitat (Walston et al., 2009). Cheatgrass (*Bromus tectorum*), an invasive species, and wildland fire also reduced the abundance of sagebrush shrublands (Bradley et al., 2006; Knick et al., 2003). Climate presents another important challenge to these ecosystems (Brown et al., 1997; Munson et al., 2011). Most shrubland components in semiarid lands are vulnerable to climate

variations, especially to precipitation changes, because precipitation effects on plants are mediated primarily by the distribution and dynamics of soil water interacting with species' roots, which usually exist in low soil moisture content (Reynolds et al., 1999; Weltzin et al., 2003; Schwinning et al., 2005). Furthermore, variations in precipitation strongly influence arid and semiarid land plant composition and dynamics (Branson et al., 1976; Cook & Irwin, 1992; Pelaez et al., 1994; Reynolds et al., 2000; Xian et al., 2012b), even at higher elevations (Guida et al., 2014). The long-term climate data analysis shows that for the period 1895-2011 in the northwest region, the most recent 35 years have included a few very wet years, including the wettest year on record in 1996 (Kunkel et al., 2013). However, the majority of recent years have been below the 1901-1960 average, including the multi-year dry periods of 2007-2009 and 2000-2002. General precipitation trends in these regions have not shown statistically significant trends for any season. However, temperatures have generally been above the long-term average for the last 25 years, both annually and for all four seasons.

Increasingly, the decline in the spatial extent and deterioration in the quality of shrubland ecosystem components reduces the ability of shrubland to provide the same level of ecosystem services in arid and semiarid lands. Improved characterization and monitoring of shrubland ecosystem components is needed to facilitate natural resources management against more complex future dynamics (Hemstrom et al., 2002). Furthermore, the information can be used to assess and monitor changes in shrubland through time and across large geographic areas. However, for highly heterogeneous shrubland ecosystems, vegetation cover usually has a large range of variability from land dominated by bare ground to areas of high density shrubs. Also, it can be difficult to quantify true cover amounts of different components using only thematic land cover characterization because highly heterogeneous vegetation components such as herbaceous, sagebrush, and shrub usually occur in close approximation. This results in large uncertainties for biomass estimates and change assessments. For better addressing the spatial distributions of shrubland components, these components need to be characterized as continuous fields (Xian et al., 2013).

Traditional field-based methods used to assess and monitor spatial distributions of shrubland components have limitations in accuracy, efficiency, and consistency (Olsen et al., 1999). Field observations are generally confined to short-term field measurements with limited samples from

limited sampling sites. Given their vast geographic extents and complicated nature of shrubland ecosystems, remote sensing data that have large area coverage and frequent acquisition cycle are often preferred to inventory, monitor, and characterize shrublands. These efforts include the use of high-resolution remotely sensed data such as QuickBird imagery (Laliberte et al., 2004), aerial photography (McGlynn & Okin, 2006), ground-based natural color vertical photography (Stow et al., 2008), LIDAR data (Mitchell et al., 2011; Sankey & Bond, 2011), and radar data (Huang et al., 2010). There are trade-offs with remotely sensed data between resolution and the extent of area imaged, with high resolution data capturing small extents and low resolution data capturing large extents. Usually, high-resolution imagery can characterize shrubland components with higher accuracy but represent small extents. Other applications have adopted medium resolution Landsat data (Viedma & Medliá, 1999; Wallace et al., 2003; Ramsey et al., 2004; Homer et al., 2009; Sivanpillai et al., 2009; Hamada et al., 2011; Vogelmann et al., 2012; Xian et al., 2012a; Hamada et al., 2013; Sivanpillai & Ewers, 2013; Sant et al., 2014) or MODIS imagery (Wallace et al., 2008) to assess spatial cover and distribution of shrubland components at a relatively large scale. The recent developments in estimating shrubland components as continuous fields using medium resolution Landsat imagery and regression tree (RT) models has been effectively demonstrated for large-scale areas (Homer et al., 2012; Xian et al., 2013). However, these approaches were restricted to functioning with one individual Landsat path/row at a time and limited the potential to scale up to large areas that extending beyond Landsat path/row extents. In order to operationally cover larger geographies, it is necessary to find approaches that can handle multiple Landsat scenes for a much larger geospatial extent than a single Landsat path/row.

Generally, mosaicking images from multiple path/rows can improve the efficiency of a large area mapping effort by optimizing ground training data and allowing classification to be performed on the whole mosaic for a large area. However, phenological differences between scenes of different dates affect the quality and accuracy of the modeling when the common mosaicking approaches are used for RT model products.

To reduce phenological effects for image change detection, different normalization approaches, including spectral information of an entire Landsat image (Yang & Lo, 2000; Xian et al., 2009) and relative radiometric normalization (Elvidge et al., 1995; Jensen, 1996; Du et al., 2001), have been attempted to match image radiometric signals so that they are consistent between images. However, the scene-based linear regression normalization usually fails to

represent the complexity of pixel-level differences for images acquired from neighboring paths/rows with different dates. Relative radiometric normalization, especially overlap regression normalization methods, have been shown to produce consistent radiances in overlap regions between scenes to produce a visually seamless mosaic. Theil-Sen regression, which provides unbiased regression line fits in the presence of measurement errors in both variables in contrast to classical linear regression approaches, has been implemented for Landsat ETM+ normalization (Olthof et al., 2005). The method uses the median of all slopes of unique pairwise observations as the maximum likelihood slope for the regression and is robust without performing procedures to detect or remove outliers prior to regression. However, the Theil-Sen regression method heavily relies on the median slope to form simple linear regression equations. The median slope-based regression equations might not effectively represent complicated landscape conditions for shrubland ecosystems and phenological differences in the normalized mosaic could result in biases for the continuous field quantification. Different radiometric balancing methods are required in order to characterize shrubland ecosystem components for a large geographic extent with Landsat data in a more robust manner.

Another challenge of estimating shrubland component distributions at a large scale using remote sensing data and modeling is how to incorporate external constraints such as climate and ecological conditions to improve model estimates. The large spatial extent covered by several Landsat images in the western United States, for example, usually contains several climate zones (Peel et al., 2007). Populations of shrubland ecosystems persist within a range of climatic conditions known as their climate envelope. The climatic regime can serve as a sensitivity proxy for revealing the variability and the spatial distribution of shrubland ecosystems that are primarily controlled by local thermal and moisture regimes. It is therefore often necessary to characterize climate features into different regions where shrubland ecosystems are situated within a relatively homogeneous climate regime. However, the RT models are usually influenced by dominant cover ranges of a target component that might exist in one or two climate or ecological zones. The modeling result, therefore, might not be able to effectively represent the spatial distributions of different shrubland components, especially when components are non-uniformly distributed and extends across several ecological regions. Including climate condition in large-scale shrubland component modeling procedure may be key to locally stratifying shrubland ecosystem components successfully across large geographic extents.

Our overall goal is to explore a method that can integrate both field samples and remote sensing data to characterize shrubland ecosystem components as continuous fields in a large geographic extent. In this study, we focus on several specific objectives. First, we hypothesize that phenological effects of adjacent Landsat images can be reduced by using a multi-variant regression approach. Newly released Landsat 8 images acquired from different paths/rows on different dates are used to generate seasonal seamless phenological mosaics for the entire study area. A phenological mosaic generated from images in a specific season represents a particular phenological state of the area. Second, we explore the use of Landsat phenological mosaics to estimate shrubland components in a consistent and robust manner. Third, we evaluate a climate zone modeling approach to enhance the modeling procedures to better characterize spatial distributions of shrubland components. The study area is divided into three different climate zones based on their long term precipitation and temperature records and the modeling procedures is performed by different climate zones. Fourth, we test to use Landsat NDVI data to create objective thresholds to define the maximum potential shrubland boundary. Finally, we conduct accuracy assessments using field data and cross validation using modeling results from high-resolution images. Nine shrubland ecosystem components, including percent annual herbaceous cover, percent bare ground cover, percent big sagebrush (*Artemisia tridentata*) cover, percent herbaceous cover, percent litter cover, percent sagebrush (*Artemisia spp.*) cover, percent shrub cover, and sagebrush and shrub heights in centimeters, are quantified at 30-m resolution and validated using an independent validation dataset. The results of spatial distributions and cover intensities of shrubland components in the study area are analyzed and documented.

2. Study area

The study area is located in the northwestern United States and contains parts of north-central Nevada, northeastern California, southeastern Oregon, and southwestern Idaho. The total area is 163,470 km² and falls within six Landsat WRS-2 footprints (Fig. 1). Elevation varies from about 600 m in valleys to 3,000 m at mountain tops. In some high elevation mountains, forest cover is the major vegetation type. This region includes the northwestern portion of Great Basin rangeland where sagebrush steppe is the major vegetation cover. Isolated pinyon-juniper woodlands, pine forests (particularly in the Sierras and Cascades), and salt-desert shrublands are

also present. The study area contains portions of nine EPA level III ecoregions including Central Basin and Range, Northern Basin and Range, Snake River Plain, Eastern Cascades Slopes and Foothills, Cascades, Sierra Nevada, Idaho Batholith, Blue Mountains, and Klamath Mountains/California High North Coast Range (Omernik, 1987).

(Insert Fig.1 here)

The mean annual precipitation in the area is about 420 mm, varying from 2,150 mm to 116 mm, according to the climate record between 1980 and 2012 (Thornton et al., 2000), and has a strong positive correlation with elevation (Wagner et al. 2003). Approximately 81% of annual precipitation occurs from November to May, and the driest months are June and July when monthly mean precipitation is often below 7 mm. The same climate dataset shows that the annual mean temperature is about 8.2°C, with a maximum and minimum of 12.5°C and 1.2°C, respectively. The warmest month is July (19.8°C) and the coldest month is December (-1.7°C). Generally, the area has dry, hot summers, but other seasons are wet and cold.

The most xeric vegetation types within the study area are the salt-desert shrublands, occurring mostly in the south. Many of its species are halophytes, with vegetation gradients radiating from salt flats based on salinity levels. At elevations less than about 1,500 m, dominant species include saltgrass (*Distichlis stricta*), greasewood (*Sarcobatus vermiculatus*), sickle saltbush (*Atriplex falcata*), and green molly (*Kochia americana*). In the less saline areas, elevated above salt flats, shadecale (*Atriplex confertifolia*), winterfat (*Ceratoides lanata*), and budsage (*Artemisia spinescens*) become more common.

Further north and/or at higher elevations above ~1,500 m, the semi-desert sagebrush type becomes dominant, including much of the Nevada portion of the study area (West and Young 2000). The vegetation type becomes sagebrush steppe as the cover of perennial grasses and forbs increases (Wagner et al. 2003). The dominant species are big sagebrush (*Artemisia tridentata*) and perennial shrub mostly under 1 m in height. Big sagebrush is divided into three subspecies based on moisture availability and topography, but we treat it as one species in this study. Associated species in sagebrush types include bitterbrush (*Purshia tridentata*), rabbitbrush

(*Ericameria nauseosa*), hop sage (*Grayia spinosa*), and black sage (*Artemisia nova*). Other sagebrush species are also found, including low sagebrush (*Artemisia arbuscula*) and threetip sagebrush (*Artemisia tripartita*). Annual species are also observed, including cheatgrass (*Bromus tectorum*), which is treated as annual herbaceous in this study, tansy mustard (*Descurainia pinnata*), and halogeton (*Halogeton glomeratus*). Perennial grasses, which live for more than two years and are treated as herbaceous, include Sandberg bluegrass (*Poa secunda*), squirreltail (*Elymus elymoides*), and crested wheatgrass (*Agropyron cristatum*).

The Snake River Plain of Idaho and Oregon in the far north of the study area has the lowest elevations of the area and is relatively hot and dry. Much of this landscape has been converted to irrigated agriculture, with much of the remaining sagebrush steppe being degraded by exotic invasive cheatgrass. Further upslope ($> \sim 1,850$ m) (West & Young, 2000), pinyon pine-juniper woodlands cover the midslopes of many mountain ranges. Mountain mahogany (*Cercocarpus ledifolius*) and manzanita (*Arcostaphylos* spp.) are also common in this zone, the latter only occurring in the Oregon and California portion of the study area. The alpine zone with the study area is minimal in extent, and typically begins at $\sim 2,800$ m (lower in the Sierras and Cascades).

3. Field samples and remote sensing data

3.1 Remote sensing data

Two types of remote sensing data were used. One is commercially available WorldView-2 (WV-2) imagery that has 8 spectral bands at 2-m nominal resolution. The high spatial resolution and multispectral bands, especially in red edge and near infrared, made WV-2 imagery useful to enhance the discrimination of shrubland components (Xian et al., 2013). The footprint of a WV-2 scene used in this study is approximately 20 km by 15 km. Twenty-five WV-2 images were acquired from May to September in 2013 and their spatial locations are shown in Fig. 2. The second remote sensing dataset is from Landsat 8, which launched in February 2013. Landsat 8 carries the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) (Landsat 8, 2013). The higher signal-to-noise performance of Landsat 8 data provides potential to improve shrubland mapping over earlier Landsat sensors. Landsat 8 bands used in this study area were 1 to 7, which have a spatial resolution of 30 meters, and thermal band 10, which was resampled to

30 m from its original 100 m resolution. Landsat 8 images were acquired from six paths/rows in 2013 (Fig. 2 and Table 1). All data were processed to Standard Terrain Correction (Level 1T). Images from the OLI sensor bands 1 to 7 were further processed to top-of-atmosphere (TOA) reflectance following the Landsat 8 standard protocol using radiometric rescaling coefficients provided in the product metadata file (Landsat 8, 2013).

(Insert Fig. 2 here)

(Insert Table 1 here)

3.2 Field measurement protocols

Field samples are essential to serve as the ground-true information for successful high-resolution modeling. Field sample locations were identified within WV-2 image footprints and the locations of WV-2 scene acquisitions were determined based on a suite of factors, including (1) accessibility by road, (2) public land concentration, and (3) presence of appropriate ecological gradients in the context of the entire study region. Areas overlapping between Landsat scenes were also preferred. We avoided areas of greater than 30% tree canopy cover, non-target land covers determined from NLCD 2006 land cover (Fry et al., 2011), and private land. Twenty-five sites that had the highest proportion of area within the target criteria were selected as potential WV-2 collection sites. Efforts were made to include sites within each level 3 ecoregion that have a wide range of elevation and that best represent all major ecological and geological features. Furthermore, a spring NDVI map derived from 2013 Landsat 8 imagery for the entire study area was parsed into 35 clusters, and the values in each preliminary WV-2 collection site were extracted to ensure the entire range of vegetation productivity and site conditions were represented.

While it would be preferable to predetermine field sampling points directly on the WV-2 imagery that we used for modeling, the time to acquire WV-2 was prohibitive. We therefore accessed existing high-resolution (1-m) orthoimagery for each WV-2 footprint (i.e., WV-2 collection site) from the USGS EROS Center (<https://lta.cr.usgs.gov>). Orthoimagery was mosaicked and an unsupervised classification was conducted to classify the imagery into 25

clusters per WV-2 collection site. Next, areas were masked out following the criteria used to select WV-2 scene acquisitions. Finally, field sample sites were identified within the remaining unmasked areas by randomly placing four points per cluster.

Field data collection consisted of both training and validation samples. Training samples, including all nine components described in the introduction section, were collected over all areas following our previous protocol (Xian et al., 2013), but a 1-m² quadrat was used instead of a 2-m² quadrat. Since our objective was to characterize the component covers/heights within a 10 by 10 m plot area, not 2-m pixels directly, the use of 1-m² quadrats was appropriate. One quadrat was centered on a randomly located point, and 4 additional quadrats were located 5 m away in all four cardinal directions. Most plots were centered on randomly selected points, but additional plots were added *ad hoc* to represent critical/unique areas that would otherwise be unsampled. We used Garmin GPSMAP 60 units, with a nameplate horizontal accuracy of 3.048 m to navigate to and mark the center point of each plot. The observations of component cover at each of the five quadrats within each 10 by 10 m plot were averaged. This average plot value for each component was subsequently rasterized into 2-m pixels (i.e. 25 pixels per plot), all assigned with the plot average component value. The spatial alignment of each plot was verified against WV-2 imagery. Each WV-2 image contained approximately 60 field plots, and a total of 1,625 samples were collected. Some field samples were collected in woodlands where the shrubland components were observed in forest openings. No field samples were collected in areas in which the total tree cover was greater than 30% at the 30-m scale.

For the independent validation sample collection, five 5-km radius sites outside of WV-2 collection areas were randomly selected for data collection. At each site, 10-15 points were randomly placed within an area that was (1) publicly owned land and (2) between 50 and 500 m from the nearest road. In total, our independent validation consisted of 95 independent observations. The sampling protocol at each validation site consisted of seven 1-m² quadrats placed every 5 m along a 30-m transect. The randomly selected points served as the starting point of each transect with the transect direction also randomly chosen. The seven observations of nine components along the 30-m transect at each point were averaged and converted to a 30-m resolution pixel.

4. Methodology

Methods designed for this study consist of several procedures including field measurement protocol, high-resolution modeling, radiometric balancing and phenological mosaicking for Landsat 8 imagery, climate zone classification, shrubland masking, Landsat scale modeling, and product validation. Fig. 3 is a flowchart illustrating the conceptual procedures used to quantify shrubland components for a large geographic extent.

(Insert Fig.3 here)

4.1 WV-2 image processing and modeling

Field data samples were used as training datasets to estimate fractional cover of different components with WV-2 imagery. To classify the value of all nine components within WV-2 footprints, we used Cubist software (<https://www.rulequest.com/cubist-info.html>), which is based on regression tree (RT) algorithms, to create regression models (Xian et al., 2013). (Use of any trade, product, or company names is for descriptive purposes only and does not imply endorsement by the U.S. Government. Limited information on this program can be found at <http://www.rulequest.com>.) RT models are rule-based predictive models, in which a multivariate linear model is associated with a rule. A training dataset which contains a dependent variable and several independent variables is required to constrain the parameters in each linear regression equation. The RT models detect correlations of the responding variable (dependent variable) to the controlling variables (independent variables) at a specific condition (Homer et al., 2012; Xian et al., 2013). Parameters used for the Cubist to create regression tree models differed for different components and in different collections. Generally, our default choices according to experiences from the previous application were five committee members, 500 maximum rules, and selection of unbiased rules (Xian & Homer, 2010). A 10% extrapolation was also used to elevate prediction at the higher end. These parameters were chosen because they allow the model to handle all possible conditions. Generally, all eight WV-2 bands were used as the controlling variable and the rasterized field data as the responding variable. The resultant RT models were implemented across the WV-2 footprint for each of the nine components. The modeling procedure was conducted for every WV-2 collection site.

The WV-2 scale modeling was focused on shrubland only. To isolate shrubland, it was necessary to remove non-shrubland features including cloud and shadow cover, urban areas, water bodies, and forests. An unsupervised classification was conducted to cluster each WV-2 image into 50 classes. Each class was manually screened to determine those non-shrubland features. In addition to the cluster-exclusion, limited manual editing was used to eliminate some cloud/shadow cover, urban areas, and agricultural lands that were left from the unsupervised classification process. Areas underlain by the target WV-2 clusters were merged with the manually edited areas to produce the final WV-2-scale mask. Next, four components estimated in the WV-2 scale including bare, herbaceous, litter, and all shrub cover predictions were summed. Areas where the sum was less than 90% or greater than 110% were assumed to be poor training areas and were masked out. The resulting raster products were spatially aggregated to 30-m resolution to serve as training data for Landsat-scale modeling.

4.2 Landsat 8 image phenological mosaic

Six Landsat 8 scenes from six paths/rows were required to cover the study area. A modeling approach based on a single Landsat scene was deemed too labor intensive because the modeling procedures need to be repeated in each Landsat scenes. The estimates of each shrubland component from individual path/row need to be edge matched when they are mosaicked. Therefore, the post-mapping process also requires a tremendous workload since multiple components are involved. The workload is substantially increased when a larger areal extent is involved. One feasible method is using the image mosaic rather than single image scene. However, a challenge for the image mosaic approach was to produce a seamless mosaic from images acquired from different paths/rows on different dates. Traditional approaches including a feathering or average technique (Jensen, 1996) were discarded for our applications due to the blurring and poor performance on eliminating phenological differences, especially when considering our large-areal mapping involving multiple Landsat scenes from different paths/rows.

An overlap radiometric balancing approach was tested to process individual Landsat scenes in different paths/rows from the same season so that the mosaic of multiple scenes from different dates would have limited phenological effects, resulting in a visually seamless mosaic. The approach focused on the overlap regression, conceptually similar with the previous overlap

regression normalization (Olthof et al., 2005), which adjusts the radiometric properties of target image(s) to match those of neighboring reference image(s) at the pixel level rather than at the scene level using the information from the overlap area, except a multivariate regression tree approach was developed for this study. The similar RT models performed by Cubist are used to build connections between target and reference images by hypothesizing that landscape properties are relatively stable and radiometric properties are similar in the overlapping area between neighboring Landsat scenes. Ideally, after radiometric balancing, the two neighboring images would be nearly identical in the overlap area. Therefore, every image band in a target image $T_i(x, y)$ was corrected into a reference image $R_i(x, y)$, $i=1, 2 \dots 8$ in the overlapping area. The differences between the final values in the overlapping area are minimized in the least squares sense:

$$\varepsilon_i = \sum (R_i(x, y) - \widehat{T}_i(x, y))^2 \quad (1)$$

where $\widehat{T}_i(x, y)$ is the spectral value of $T_i(x, y)$ after the radiometric balancing.

The same parameters that were used for WV-2 modeling were used here except maximum rules were increased to 600 and no extrapolation was allowed. For neighboring images, training samples were then randomly acquired from the reference Landsat 8 image in the overlapping area. The controlling variables included radiometric data from all seven bands of the target image. After that, RT models were created based on rules and correlation levels between the controlling variables and the responding variable for each individual band. Subsequently, regression models were implemented to each of the spectral bands for all pixels to extrapolate radiometric balancing image(s). The balancing images were further checked to remove any biases, which were identified as values either larger than 140% of the maximum or smaller than 30% of the minimum of the original three-season magnitude, potentially introduced by local over-fitting of the regression models. These values were replaced by the original values of the image. The thermal band (band 10) of the target image was also processed following the same procedure as for the spectral bands, except band 10 of the reference image was added in the controlling input and the responding variable is band 10 of the target image(s). The radiometric balancing images were then mosaicked with reference images to produce a phenological mosaic that covers the entire study area. Three seasonal mosaics (spring, summer, and fall) were created for the spectral bands and only a spring mosaic was produced for the thermal band.

4.3 Maximum potential shrubland mask

Shrubland components occur at various densities and are often mixed with other land cover types which can potentially confound detection, especially in forested area where tree canopy cover is relatively low and the reflectance of tree or shrub canopy is often similar. Since our objective was to map shrubland components wall-to-wall across the study area, the fractional cover of shrubland components quantified from regression models potentially include in-valid areas such as forested and agricultural areas our models were not designed to address. Therefore, it was necessary to characterize a mask to identify non-shrub areas such as forests, urban and agriculture, that can be eliminated from modeling consideration and ensure final products represent appropriate areas.

A hierarchical constraint approach was used to define extents of non-shrubland that we excluded from our modeling. An initial forest mask was created by using the high-resolution WV-2 classification as training data to classify non-shrubland using Landsat 8 images and derivatives. The WV-2 classification was separated into forest and non-forest cover and resampled to 30 m following approaches discussed in section 4.1. The derivatives of Landsat 8 images included the Normalized Difference Vegetation Index (NDVI) and Modified Soil-Adjusted Vegetation Index (MSAVI) that were calculated for each season (spring, summer, and fall). The resampled WV-2 forest mask grid cells were used as sampling points to extract seasonal vegetation indices from the NDVI and MSAVI data layers and further to create a cross table matrix. We then created two different forest masks by coupling these data with the NLCD 2011 land cover classification (NLCD, 2011). First, within each ecoregion and each of the three forest classes mapped in NLCD 2011, we identified the general “forest/non-forest” thresholds for each vegetation index. Each pixel whose vegetation index exceeded the threshold was considered as forest. Second, we used the NLCD 2011 tree canopy data to create an additional non-shrubland mask by identifying areas with greater than 30% canopy cover. To do this, we regrouped the NLCD 2011 tree canopy data at 10 percent intervals from above 30% canopy cover and extracted the seasonal vegetation indices for these groups. We then adjusted thresholds of these indices for each of the tree canopy density classes. Each pixel whose vegetation index

exceeded the threshold and has tree canopy more than 30% was treated as forest. The final forest mask was generated by combining the two forest masks.

For the non-forestland mask, both NLCD 2011 and indices derived from Landsat 8 imagery were used. All urban areas, snow, and ice were directly masked out using the NLCD 2011 land cover. Cultivated crops and pastures/hay fields were masked using the 2013 Cropland Data Layer (CDL) for the United States from the National Agricultural Statistics Service (NASS) and the NLCD 2011 agricultural classes with a combination of NDVI and MSAVI thresholds that derived from high resolution training data. The mask was finalized with a minimal amount of hand editing. This mask is needed to identify the boundaries between agriculture/hay and natural non-forest vegetation (shrublands and grasslands). Landsat images and the NLCD 2011 land cover product were used to update water cover with current water level for the mask. All non-shrubland masks were validated using random samples within the study area. These samples were visually compared with mask samples using high-resolution images from Google Earth.

4.4 Classification of climate zone

Several areas that are within relatively homogeneous climate regimes were characterized as climate zones for the study area. The gridded Daymet climate data between 1980 and 2012 at 1-km resolution (Thornton et al., 2000) were used to depict climate gradients based on regional characteristics of both multi-year means of mean annual temperature and annual precipitation. Two variables of annual precipitation and mean annual temperature were used to characterize climatic condition. Both temperature and precipitation distributions were first classified into 10 clusters separately using the Iterative Self-Organizing Data Analysis Technique (ISODATA) algorithm. Subsequently, both temperature and precipitation clusters were ranked and compared to determine thresholds that were used to further aggregate the study area into three climate zones—dry and warm, moderate wet and moderate warm, and wet and cold. Consequently, RT modeling was conducted in each of the three zones independently.

4.5 Landsat scale modeling

Component predictions from the WV-2 images that were resampled from 2 m to 30 m were mosaicked for each component to serve as training data for Landsat scale modeling. Regression tree models used to map shrubland components were created using three seasons of Landsat 8 imagery and ancillary datasets including slope, aspect, and position index. The distributions of shrubland components are usually constrained by topographic features of mountain areas and elevation information is usually needed to successfully extrapolate the spatial distribution of shrubland components (Homer et al., 2012). However, the use of a Digital Elevation Model (DEM) in regression models can generate certain artifacts associated with elevation variations. In the current modeling effort, we tested the use of the Landsat 8 thermal band (band 10) as surrogate data to replace the DEM in the regression model. The nature of the thermal data distributions can still well represent elevation variation without creating DEM-related artifacts.

Shrubland components were modeled individually using different regression models. Each of nine components were characterized for each climate zone to capture their spatial distribution features in these zones. Therefore, three RT modeling procedures were conducted for each component using training samples produced from WV-2 scale modeling in each climate zone. The distributions of the component quantified from these models were valid in the same climate zone, although the estimate was performed in the entire area. The three estimates for each component were clipped out following their climate zone boundaries and were then mosaicked. To smooth the boundary, a gradient boundary smoothing (GBS) method was developed to ensure the smooth transition between different climate zones for each component when it was mosaicked. The GBS created weights that vary from a central point within the buffer zone between any two zones. For climate zone i neighboring with a zone j , the GBS was performed in a 30-pixel buffer across both sides of zonal boundaries by the following constraint:

$$mP(x_{i,k}) = x_{j,k} * N_{j,k} + \bar{P}(x_{i,k}, x_{j,k}) * M_{j,k} \quad (2)$$

where $mP(x_{i,k})$ is the smooth value of a component for a pixel k in the buffer extended from zone i , $x_{j,k}$ is the value of the same component of the pixel k in the same buffered area, and $\bar{P}(x_{i,k}, x_{j,k})$ is the mean value of the component across the buffer. $M_{j,k}$ and $N_{j,k}$ are weighted parameters with a summation of 1 and are calculated by distances extended into zones j from zone i by 30 pixels.

4.6 Validation of model estimate

The validation of shrubland component estimates was conducted in two parts: model performance and field data validation. In the model performance evaluation, three statistical measures, including average error, relative error (the ratio of the average error to the error that would result from predicting the mean value), and Pearson's correlation coefficient, were used to test model accuracy. The three measures were calculated directly by RT models using a portion of training inputs as the validation data pool (Xian and Homer, 2010). Validation was only conducted on the modeling results from Landsat scale quantification. For field data validation, independent field measurements were compared with values of fractional cover of shrubland components that were averaged in each validation plot from pixel values of the model estimate. Two parameters were calculated: root mean square error (RMSE) and normalized RMSE (nRMSE) by the following formulas:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{obs,i} - X_{mod,i})^2}{n}} \quad (3)$$

$$nRMSE = \frac{RMSE}{X_{obs,max} - X_{obs,min}} \quad (4)$$

where X_{obs} is from validation data, X_{mod} is for the value from RT models and $X_{obs,max}$ and $X_{obs,min}$ are for the maximum and minimum values of validation data for a specific component.

The shrubland mask was validated by comparing masked and un-masked areas with Google Earth at randomly selected points using a 9 by 9 moving window.

A cross validation assessment was also performed for all components using model estimates from WV-2 data to compare with model estimates from Landsat data. The portion of the WV-2 data used as model training for the Landsat scale component estimates were excluded from this validation.

5. Results

5.1 WV-2 scale modeling

The overall performances for all components using field training data and WV-2 imagery are summarized in Table 2. Overall, the RT models for bare ground and herbaceous estimates performed better than those for other components. Average errors are large for shrub height and sagebrush height estimates, but relative errors were low due to high component values. The mean cover or height of each component and their standard deviation averaged across all WV-2 footprints at 30-m resolution is also listed in Table 2. Bare ground has the largest mean cover value at 48%, while big sagebrush has the smallest mean cover value at 4.6%. The standard deviations of these two components are relatively large.

(Insert Table 2 here)

5.2 Landsat 8 phenological mosaic

Radiometric balancing for Landsat 8 images was performed for neighboring images that were acquired on different dates. Table 1 shows that image acquisition dates in paths 42 and 43 were the most consistent with all images within each path being the same date. Radiometric balancing was then applied using the image that was directly mosaicked from path 43 as the reference image for all three seasons. Same date images in path 42 were also directly mosaicked, and the seasonal mosaic was balanced to the same seasonal mosaic of path 43 using the training data in the area labeled 1-2 in Fig. 2(b). Similarly, images in path 44 were balanced to the seasonal mosaic of path 43 using the training samples in the area labeled 2-3 in Fig. 2(b). After radiometric balancing, images from paths 42 and 44 were mosaicked with the images from path 43 to produce three seasonal phenological mosaics. Fig. 4 shows a Landsat 8 phenological mosaic in summer for the entire study area (I). Enlarged images of before and after radiometric balancing in the three seasons are also displayed in Fig. 4 II and III for the two highlighted areas in Fig. 4 I. The normalized image mosaic eliminates seamlines that usually exist in neighboring images acquired on different dates and mosaicked with a traditional feathering approach.

(Insert Fig.4 here)

We evaluated the radiometric balancing of images for each individual spectral band by randomly selecting about 1,700 samples from the overlapping area labeled 2-3 in Fig. 2(b) using images acquired in July. Fig. 5(I) shows scatterplots for bands 1-7 and 10 of the target image (y axis) before the radiometric balancing against the reference image (x axis) (a-h). Generally, the target images and the reference images are similar in these spectral bands since they are from the same landscapes but in different acquisition times. Differences are observed for these samples that are far apart from the 1 to 1 lines displayed as red, especially for bands 4-7 (d-g in I), and 10 (h in I). Fig. 5(II) displays the similar scatterplots for samples obtained from the same locations as in Fig. 5(I), but the target images are replaced by the radiometrically balanced images. Generally, the radiometric balancing enhances the similarity between the target image and the reference image, especially in bands 4-7 and the thermal band. Overall, R^2 values increase about 2.3% for bands 1-7 (a-g in II) and 6.4% for band 10 (h in II).

(Insert Fig.5 here)

By checking with the radiometric balancing results in different landscapes, we found that apparent improvement in correlations were observed in bands 2 to 4 for water in summer, bands 1 to 7 in spring for barren, bands 1 to 5 for forest in spring, band 5 for shrub in spring, and bands 3 to 6 for agricultural land in spring. Fewer band correlations were improved in the fall imagery. However, summer images had the fewest improvements in correlations for all bands after balancing. The radiometric balancing reduced the most phenological differences in spring, when the phenological effect is the most profound for the area.

5.3 Non-shrubland mask

The non-shrubland mask, created to exclude areas not considered appropriate for our models, includes forest, agriculture, urban, and other areas. Our mask model eliminated 12.3% of the

study area from modeling consideration, with 87.7% of the study area available to be modeled for all shrubland components.

5.4 Climate zones and Landsat scale modeling

Our climate zone approach characterized the regional climatic conditions into three different zones. Table 3 illustrates means and standard deviations of precipitation and temperature for the entire study area, as well as for each climate zone. Mean annual precipitation and annual mean temperature for the area are 420.7 mm and 8.2°C, respectively. The mean annual precipitation for zones 1, 2, and 3 is 269.0 mm, 400.5 mm, and 668.8 mm, respectively. The standard deviation of precipitation in zones 1 and 2 is relatively small compared to that in zone 3, indicating a large variation in precipitation in the zone. The annual mean temperature in zones 1, 2, and 3 is 10.1, 7.6, and 6.6°C, respectively. Zone 3 also has the largest standard deviation in temperature.

(Insert Table 3 here)

The spatial distribution of climate zones and the fractional cover of all components quantified from zonal modeling using Landsat 8 phenological mosaics for the entire study area is exhibited in Fig. 6(a-j). The shrub mask appears in white in these graphics. Climate zone variance generally follows elevation changes within the zone (Fig. 6a). The dry and warm climate zone is generally found at lower elevations and in valleys, while the wet and cold climate zone is at higher elevations in mountainous areas. The moderate climate zone is distributed mostly in plains and relatively flat areas. Figure 6(b-j) represents spatial distributions of percent annual herbaceous cover, percent bare ground cover, percent big sage cover, percent herbaceous cover, percent litter cover, percent sagebrush cover, percent shrub cover, sagebrush height (cm), and shrub height (cm). Shrubland components, except litter cover, follow the climate boundary very well. The dry-warm zone contains higher bare ground cover and less dense vegetation cover. As water content in the ground level increases and temperature decreases, the amount of bare

ground cover changes from high to relatively low. Cover intensities of shrubland vegetation components follow a reverse change from relatively low to relatively high from climate zone 1 to zone 3. Both sagebrush and shrub heights also follow similar trends as their cover intensifies. Fig. 6 (b1-c1) and (b2-c2) show both bare ground and shrub distributions in an enlarged area displayed in Fig. 4(II) and (III). Their spatial distributions also demonstrate that phenological differences are eliminated in the continuous field estimate using the Landsat 8 phenological mosaic.

(Insert Fig.6 here)

Table 4 summarizes the results from Landsat scale modeling for all components. The average values of different components and their standard deviations for the entire area are listed. Additionally, means and standard deviations of different components in different climate zones are illustrated. Comparing Table 4 with Table 2 suggests that means and standard deviations for the study area are quantified following similar magnitudes in training datasets, in which bare ground has the largest cover percentage and big sagebrush has the smallest. Moreover, annual herbaceous and shrub height have the smallest ratio of mean to standard deviation, indicating large spatial variations are quantified for these components. By separating shrubland component distributions into different climate zones, their means of fractional cover and height in each climate zone are summarized. Annual herbaceous still has a smaller mean to standard deviation ratio in zone 1 and zone 3. Big sagebrush and sagebrush also have small mean to standard deviation ratios in zone 1. Other components do not have apparent mean to standard deviation ratios in each zone. Zonal means of all components except litter vary linearly following the climate gradient.

(Insert Table 4 here)

5.5 Validations of shrubland components

The visual comparison for the non-shrub mask found that the agreement was about 90%. Most uncertainties were found in agricultural land, mining areas, and a few water bodies.

Results from post-modeling validation are illustrated in Table 5. Bare ground has the largest r^2 value and shrub height has the smallest. Other components have a similar range in r^2 values. All components except shrub height have significant ($p<0.05$) correlations with the validation dataset. Bare ground, sagebrush height, and shrub height have relatively large RMSE values. All RMSE values are smaller than corresponding means of all components. Most components have the same range in nRMSE except the sagebrush height. Cross validations were illustrated in Table 6. The cross validation statistics suggest that Landsat scale estimates correlate with WV-2 scale modeling results very well with relatively large r^2 and small nRMSE values.

(Insert Table 5 here)

(Insert Table 6 here)

6. Discussion

Shrubland component mapping based on field measurements, high-resolution WV-2 imagery, Landsat 8 imagery, and continuous field modeling has been conducted in the northwestern Great Basin area, where shrubland is the dominant land cover, in the United States. The results suggest that estimating shrubland components as continuous variables can characterize these components with reasonable spatial distributions and cover intensities over a large geographic area. High-resolution WV-2 images were essential for creating the training data pool, and medium resolution Landsat 8 images were useful for the quantification in a large geographic extent (Homer et al., 2012; Xian et al., 2013). The comparison of accuracy assessment shows that the means of r^2 and RMSE for the four primary components (bare ground, herbaceous, litter, and shrub) are 0.48 and 9.08 for the current study, 0.28 and 10.96 for the result from Homer et al. (2012), and 0.41 and 14.75 for the Arizona results (Xian et al., 2013). Relatively higher accuracy was achieved and efficiency was greatly improved over our previous efforts for estimates of shrubland components.

6.1 Field data protocol and WV-2 scale modeling

Good training datasets are essential for this two-phase modeling approach required to map shrubland components. The current field measurements provide accurate and consistent data, which represent both spatial distribution features and cover intensities of different components, and were collected from 1-m² quadrats placed over the randomly located sites within strategically selected collection areas. Compared to our previous field sampling method that measured quadrats in a straight transect (Homer et al., 2012) or by 2 m² quadrats (Xian et al., 2013), this method covers a smaller spatial extent and the field measurements are closer to the true distribution patterns of components at the WV-2 scale. One meter squared quadrats were appropriate for field conditions in this study area, where shrubland vegetation is usually sparse and individual shrubs are usually smaller, shorter, and less dense than those in Texas and the eastern United States. Since our objective was to determine the mean plot value, we found that a greater number of smaller quadrat observations (1 m²) produced a more accurate mean plot value in a shorter amount of time than a smaller number of 2 m² quadrat observations.

The WV-2 scale modeling was conducted separately for all 25 WV-2 collection sites using approximately 60 field plots in each WV-2 image as the training data. The high spectral and spatial resolution of WV-2 imagery enhanced the discrimination of shrubland components and resulted in relatively large r^2 values and small average and relative errors in RT models. After RT modeling, the 2-m estimates are resampled to 30 m to serve as the second phase training data. For all non-shrubland areas that were masked out from the 2-m WV-2 scale estimate, a unique number was assigned to separate them from shrubland components. When the 2-m scale products were resampled to 30 m, these masked areas were ignored rather than included as zeroes in the resampling calculation. We found that if these masked areas were labeled as zeros and included in the degradation, the resulting training data could confuse the RT models because green vegetation, such as tree canopies, was labeled as zero. When such modeling estimates were used as training datasets in the Landsat scale modeling, RT model performances were usually poor. We also noticed that the sums of primary (shrub, herbaceous, litter and bare ground) components modeled from WV-2 imagery could exceed 100% in some pixels after they were resampled to 30 m. These biases might be introduced by uncertainties in the training data or by the quality of the

WV-2 imagery. To reduce artificial effects and to maintain the training dataset consistency for the coarse scale modeling, we filtered out pixels with the sum of the fractional cover greater than 100% from the second phase training dataset.

6.2 Phenological mosaic of Landsat 8 imagery

It is important to maintain efficiency for the large-scale mapping effort using remote sensing information. For regional or national mapping activities, multiple images from different path/rows are usually needed to cover a large spatial extent. One feasible way to accomplish such a large-scale effort more efficient is using an image mosaic rather than single image scenes. The phenological mosaicking approach we introduced in this research focuses on an overall radiometric balancing between neighboring scenes acquired on different dates. It is desirable after radiometric correction to minimize radiometric differences between neighboring scenes in their overlapping zones. The RT models can build up connections between different neighboring scenes using multi-variant regression equations with information from all Landsat 8 bands for all possible constraints. Therefore, spectral values from all radiometric bands should be highly similar, or highly correlated.

The concept of using training data from the overlapping area to perform radiometric balancing is not new (Jensen, 1996; Olthof, et al., 2005; Pan et al., 2009). However, previous studies suggest that these approaches are relatively time-consuming, such as complex outlier resistant approaches (Elvidge et al., 1995; Du et al., 2001), or may not robust enough, such as Theil-Sen regression (Olthof et al., 2005), for our mapping effort. The regression tree modeling approach uses training samples that are large enough to include most land cover types defined by NLCD to represent the spectral features of neighboring images in the overlap area. However, balancing scenes may not be entirely characterized by the overlap regions. The biases may propagate across a mosaic because of cloud or haze, snow and ice melting, fires, or other land cover changes that emerge only in one image in the overlap region.

The training data acquired randomly in the overlapping region should be from stable areas and avoid areas that experienced abrupt changes during the dates that neighboring images were acquired. Ideally, image change detection should be performed for overlapping images to exclude potential change areas in the training samples. However, we only conducted visual

inspection of these images for the radiometric balancing because (1) no apparent changes in land cover were observed; (2) images in these overlap areas were cloud free; and (3) visually identified changes like snow and ice were excluded. It is worth noting that the neighboring images for radiometric balancing should be acquired in the same season to achieve the best performance for phenological mosaicking.

6.3 Characterization of climate zones

The 30-m training dataset generated from WV-2 modeling illustrates that most shrubland components in the study area have relatively large spatial variations (Table 2). For example, shrub has a mean of 13.8% and a standard deviation of 10.8. The large magnitude of standard deviation represents a wide spatial distribution pattern across the area where topographic variations are more pronounced. Results from using a single RT model for the entire area did not appropriately represent the spatial distribution features of shrubland components.

Climatic conditions have a large effect on the abundance and distribution of plant species in the semi-arid shrubland ecosystems of this region. Spatial distributions of shrubland components are highly correlated with climate influence rather than geographic locations in some mountainous areas (Cook & Irwin, 1992). Also, different shrubland components can have a unique response to climatic conditions. RT models that are constructed following different climate zones could help capture unique spatial distribution patterns of shrubland components, especially in both high and low ends, and avoid smoothing the estimate toward the middle range of the values. The mapping results also illustrate the spatial means of shrubland components and their standard deviations follow the climate zones well. Climate effects should be considered for quantifying shrubland components in such large spatial extents.

6.4 Distribution patterns of shrubland components

The use of climate zones and Landsat 8 phenological mosaics improved RT modeling performance in both efficiency and accuracy. The model validation using our field validation dataset suggests that all fractional cover estimates have relatively large r^2 values and small nRMSE values. The model estimates also illustrate shrubland components follow the climatic

gradients in the region. For example, the cover intensities of most vegetation components increase from zone 1 to zone 3. Shrub and sagebrush heights also follow the same distribution pattern. In contrast, the cover intensities of annual herbaceous and bare ground decrease from zone 1 to 3. Litter, however, does not show an apparent gradient with climate zones. The model results suggest that spatial distribution of shrubland components are sensitive to climatic conditions and have large variations following elevation changes. By using climate data with remote sensing imagery, RT models can more closely extrapolate the true distribution patterns of shrubland components. The validations performed using our field measurements suggest RMSEs of different components do not correlate well with r^2 values of these components (Table 5). However, nRMSEs illustrate certain connections with r^2 values, indicating large r^2 values usually resulting in smaller nRMSEs. The cross validations by comparing WV-2 scale model estimates that were not used in training with Landsat scale modeling results and were to be treated as true measurements suggest that the Landsat scale modeling follows the general patterns of WV-2 scale estimates with relatively higher correlations and lower values in both RMSE and nRMSE (Table 6). For the four primary components (bare ground, herbaceous, litter, and shrub), the averages of r^2 , RMSE, and nRMSE were improved from 0.368, 8.305, and 0.165 in independent validation to 0.683, 6.73, and 0.08 in cross validation. Data used for cross validation represent the spatial distributions and are more comparable to the modelled results. The uncertainties of the measurements represented by RMSE and nRMSE were then reduced and relative statistics illustrated by r^2 values were improved. The independent validation data could be more to blame for the weak correlation than the spatial products and relatively large RMSE and nRMSE in independent validation. Specifically, the locations of our validation points were determined using a randomization approach including the locations of validation sites and validation points where validation data were collected. We think that the stage of randomization (i.e., placement of points within sites) can be improved by eliminating highly heterogeneous (e.g., those with a high local-scale standard deviation) areas from consideration in random point placement. Doing so will increase the comparability of ground sampled validation data to the modelled results.

7. Conclusion

The approach presented in this paper was used to efficiently estimate the fractional cover of shrubland components of annual herbaceous, bare ground, big sagebrush, herbaceous, litter, sagebrush, shrub, sagebrush height, and shrub height across a regional extent in the northwestern United States. Field surveys were required to initially measure different shrubland components, and the spatial distributions of these components were then modeled as continuous fields using a two-phase approach that involved both high and medium resolution remote sensing data. Radiometric balancing was developed to correct radiometric differences between neighboring images allowing a phenological mosaic to be produced from multiple images acquired on different dates and from different Landsat path/rows. The seamless mosaic covers the entire study area and the use of the image mosaic in RT models greatly improves modeling efficiency. This method is most useful when a seamless phenological mosaic is needed to cover a large region. Our climate zone modeling approach for Landsat-scale mapping improves modeling accuracy by capturing cover intensities and characteristics of the spatial distribution of all shrubland components. We conclude that the approach presented in this large-scale effort can serve as a framework to further quantify shrubland components as continuous fields for NLCD.

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List of Figure Captions

Fig. 1 Study area located in the northwestern conterminous United States. Boundaries and names of Level III Ecoregions within the study area are also displayed.

Fig.2 Elevation, Landsat 8 path/rows, locations (black squares) of acquired WV-2 imagery, and locations of collection sites of independent validation data (a). Overlap areas of Landsat scenes for radiometric balancing (b). The areas 1, 2, and 3 represent paths 42, 43, and 44. Their corresponding overlap areas are labeled as 1-2 for paths 42 and 43 and 2-3 for paths 43 and 44.

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Fig. 6 Climate zones (a), percent annual herbaceous cover (b), percent bare ground cover (c), percent big sage cover (d), percent herbaceous cover (e), percent litter cover (f), percent sagebrush cover (g), percent shrub cover (h), sagebrush height (i), and shrub height (j) for the study area. The zoomed in graphics (b1-c1) and (b2-c2_ are shrub and bare in the lower left square area in Fig.4 (II) and in the upper right squared area in Fig.4 (III).

Table 1 Landsat 8 paths/rows and acquisition dates used in this study.

Path/Row		42/30	42/31	43/30	43/31	43/32	44/31
Season/Date	Spring	06/05/201	06/05/201	06/28/201	06/28/201	06/28/201	06/03/201
		3	3	3	3	3	3
	Summer	07/07/201	07/07/201	07/14/201	07/14/201	07/14/201	07/05/201
		3	3	3	3	3	3
	Fall	09/09/201	09/09/201	08/15/201	08/15/201	08/15/201	09/07/201
		3	3	3	3	3	3

Table 2 Regression tree model performance using WV-2 imagery. Performance is measured by average error (Avg. Error), relative error (Rel. Error), and correlation coefficient R for percent cover and height (cm). Mean values for cover percent or heights (cm) and standard deviations (σ) of all WV-2 scale estimates in 30 m are also listed.

Component	Avg. Error	Rel. Error	R	Mean	σ
Ann. herb.	2.30	0.31	0.92	7.3	9.3
Bare	5.34	0.25	0.95	48.0	21.9
Big sagebrush	2.21	0.34	0.86	4.6	5.2
Herb.	3.63	0.29	0.94	20.4	13.6
Litter	3.49	0.32	0.93	17.2	8.0
Sage	3.00	0.33	0.86	8.2	7.1
Shrub	3.60	0.28	0.93	13.8	10.8
Sagebrush hgt.	7.32	0.33	0.89	17.0	23.6
Shrub hgt.	9.14	0.30	0.89	38.9	33.2

Table 3 Mean annual precipitation (mm), annual mean temperature (°C), and their standard deviations in the study area and three climate zones.

	Precipitation		Temperature	
	Mean	Standard Deviation	Mean	Standard Deviation
All zones	420.7	183.7	8.2	1.6
Zone 1(dry and warm)	269.0	64.2	10.1	0.8
Zone 2 (moderately wet and warm)	400.5	63.5	7.6	0.8
Zone 3 (wet and cold)	668.8	228.9	6.6	1.7

Table 4 Percent cover, height (cm), and standard deviations (σ) of shrubland components in the study area and in different climate zones.

Component	All area		Zone 1		Zone 2		Zone 3	
	Mean	σ	Mean	σ	Mean	σ	Mean	σ
Ann. Herb.	9.6	7.7	10.5	8.7	10.3	7.2	6.1	6.7
Bare	48.4	19.1	56.9	19.6	49.7	15.4	30.9	17.3
Big sage	5.7	4.3	4.3	3.9	5.9	4.0	7.0	5.3
Herb.	19.6	12.0	15.9	12.5	20.4	11.1	23.1	12.4
Litter	17.6	6.9	18.8	8.2	16.4	6.1	19.4	6.1
Sage	8.7	6.0	5.5	4.7	9.7	5.6	10.3	7.3
Shrub	14.4	10.5	8.9	5.9	13.5	8.1	25.6	13.5
Sagebrush	27.8	18.5	22.2	17.3	29.4	17.9	32.0	20.4
hgt.								
Shrub hgt.	43.6	38.1	35.2	20.4	35.7	23.3	80.6	64.4

Table 5 Independent validations of Landsat-scale modeling performed by comparing field observations and model estimates. All components except shrub height have significant correlation with the validation data at $P \leq 0.01$ for all 90 samples. Shrub height does not correlate with the validation well.

	r^2	RMSE	nRMSE
Ann.herb.	0.31	5.33	0.17
Bare	0.56	10.04	0.15
Big sagebrush	0.22	3.76	0.19
Herb	0.38	7.52	0.17
Litter	0.19	6.73	0.18
Sage	0.41	4.25	0.16
Shrub	0.34	8.93	0.16
Sagebrush Hgt.	0.17	14.57	0.20
Shrub Hgt.	0.03	45.48	0.18

Table 6 Cross validation by comparing Landsat-scale model estimates with WV-2 model estimates with 8805 samples. All components have significant correlation with the validation data at $P \leq 0.01$.

	r^2	RMSE	nRMSE
Ann.herb.	0.77	4.97	0.08
Bare	0.79	9.25	0.09
Big sagebrush	0.56	3.19	0.07
Herb	0.74	6.65	0.07
Litter	0.58	5.24	0.09
Sage	0.60	4.12	0.08
Shrub	0.62	5.78	0.07
Sagebrush Hgt.	0.45	14.08	0.11
Shrub Hgt.	0.65	17.28	0.05

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