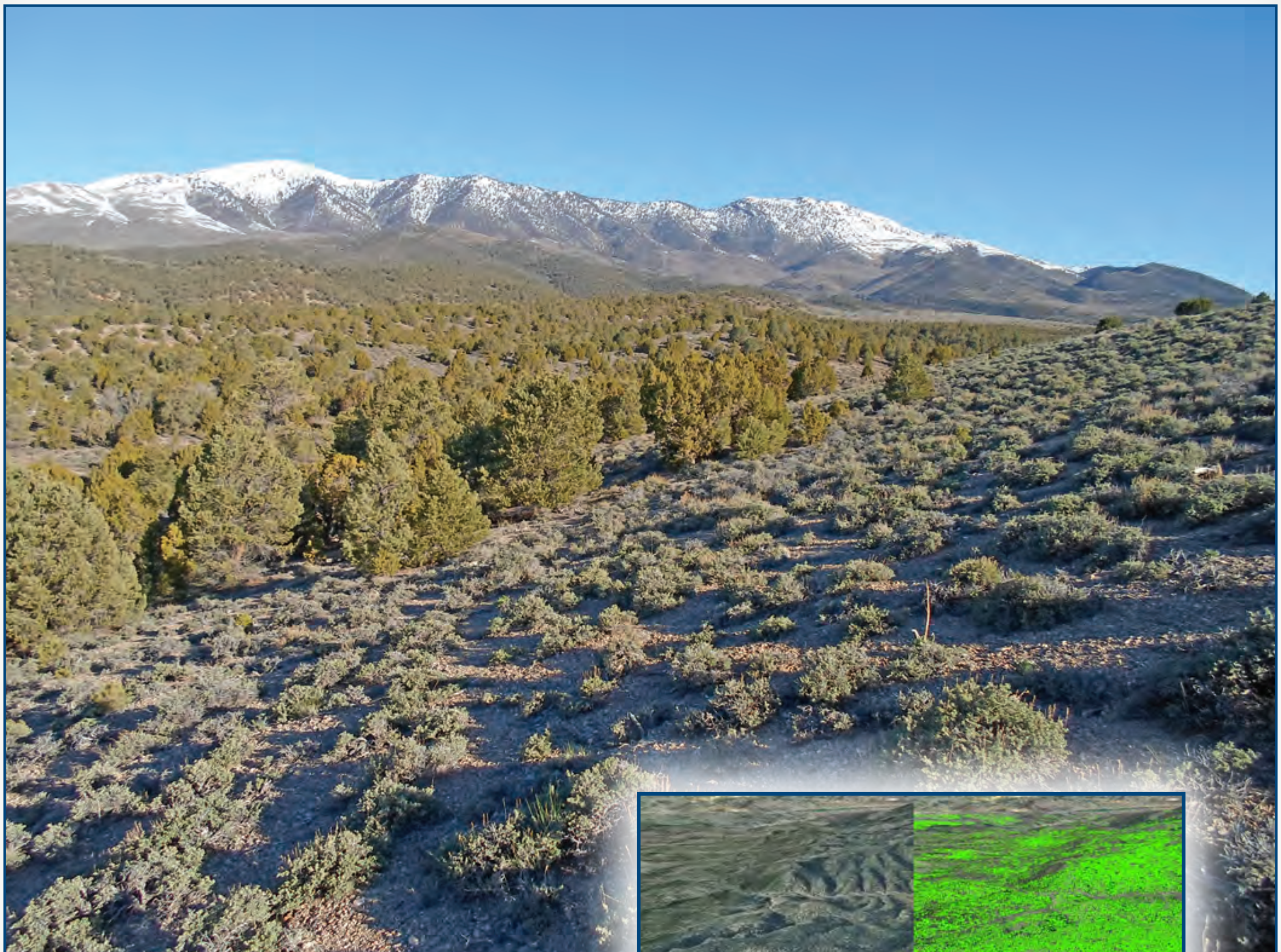
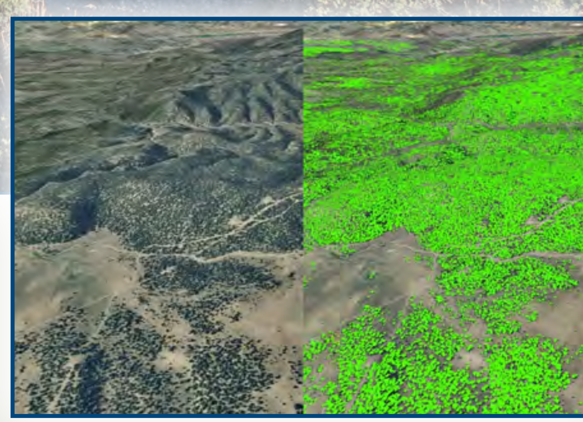
Prepared in cooperation with the Bureau of Land Management and Nevada Department of Wildlife

Using Object-Based Image Analysis to Conduct High-Resolution Conifer Extraction at Regional Spatial Scales





Open-File Report 2017–1093

U.S. Department of the Interior
U.S. Geological Survey

Cover:
Background: Photograph showing conifers in sagebrush ecosystem on southern side of Spruce Mountain, northeastern Nevada, May 1, 2014. Photograph by Steven Hanser, U.S. Geological Survey.
Inset: Image showing automated feature extraction of conifer trees in Nevada.

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By Peter S. Coates, K. Benjamin Gustafson, Cali L. Roth, Michael P. Chenaille, Mark A. Ricca, Kimberly Mauch, Erika Sanchez-Chopitea, Travis J. Kroger, William M. Perry, and Michael L. Casazza

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Preface

This report was developed to provide scientific and corresponding spatially explicit information regarding the distribution and abundance of conifers (namely, singleleaf pinyon [*Pinus monophylla*], Utah juniper [*Juniperus osteosperma*], and western juniper [*Juniperus occidentalis*]) in Nevada and northeastern California. Distributional expansion of conifers into sagebrush ecosystems over the past 150 years is a significant threat to greater sage-grouse (*Centrocercus urophasianus*; hereinafter, "sage-grouse") populations, as well as those of other sagebrush obligate species. Accordingly, we mapped conifers at a high resolution (1 meter) and derived multiple products (available at https://doi.org/10.5066/F7348HVC) within sage-grouse habitats of Nevada and northeastern California. These products are intended as decision support for land managers, policy-makers, and interested stakeholders to be used for a variety of management and research applications. Users also have the ability to set custom bins representing user-desired ranges of conifer cover for their own applications.

Acknowledgments

This project was supported by the Nevada Sagebrush Ecosystem Program, Nevada Department of Wildlife and Bureau of Land Management. We thank the U.S. Forest Service and California Department of Fish and Wildlife Service for logistical coordination. We extend particular gratitude to reviews of previous manuscript drafts by S. Hanser, C. Overton, and T. Kimball, U.S. Geological Survey. This project would not have been possible without the help of numerous geographic information system (GIS) technicians, student interns, and volunteers who worked day and night to complete this work, particularly R. Battersby, G. Dunning, A. Javad, C. Lewis, M. Lopez, K. Peterson, D. Podolsky, C. Quispe, T. Stinchfield, and B. Zhou, U.S. Geological Survey, for providing technical assistance. We are also grateful to D. Delehanty (Idaho State University), as well as L. Parker and C. Hettich, U.S. Geological Survey, for logistical support and contributions. We also thank the Center for Geographical Studies at California State University Northridge for contributing to conifer extraction, and to Overwatch Systems, Ltd., for technical support.

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Conversion Factors

International System of Units to Inch/Pound

Multiply	By	To obtain
	Length	
meter (m)	3.281	foot (ft)
kilometer (km)	0.6214	mile (mi)
	Area	
square meter (m^2)	0.0002471	acre
hectare (ha)	2.471	acre

Datum

Horizontal coordinate information is referenced to the North American Datum of 1983 (NAD 83).

Acronyms and Abbreviations

AFE	automated feature extraction
BLM	Bureau of Land Management
DCNR	Nevada Department of Conservation and Natural Resources
DOQQ	digital orthophoto quarter quads
FA	feature analyst
FS	Forest Service
GIS	geographic information systems
NAIP	National Aerial Imagery Program
NDOW	Nevada Department of Wildlife
OBIA	object-based image analysis
PMU	population management unit
SD	standard deviation
SETT	Sagebrush Ecosystem Tactical Team
SWA	spatial wavelet analysis
USDA	U.S. Department of Agriculture
USFWS	U.S. Fish and Wildlife Service
USGS	U.S. Geological Survey
VHSR	very high spatial resolution

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Abstract

The distribution and abundance of pinyon (*Pinus monophylla*) and juniper (*Juniperus osteosperma, J. occidentalis*) trees (hereinafter, "pinyon-juniper") in sagebrush (*Artemisia* spp.) ecosystems of the Great Basin in the Western United States has increased substantially since the late 1800s. Distributional expansion and infill of pinyon-juniper into sagebrush ecosystems threatens the ecological function and economic viability of these ecosystems within the Great Basin, and is now a major contemporary challenge facing land and wildlife managers. Particularly, pinyon-juniper encroachment into intact sagebrush ecosystems has been identified as a primary threat facing populations of greater sage-grouse (*Centrocercus urophasianus*; hereinafter, "sage-grouse"), which is a sagebrush obligate species. Even seemingly innocuous scatterings of isolated pinyon-juniper in an otherwise intact sagebrush landscape can negatively affect survival and reproduction of sage-grouse. Therefore, accurate and high-resolution maps of pinyon-juniper distribution and abundance (indexed by canopy cover) across broad geographic extents would help guide land management decisions that better target areas for pinyon-juniper removal projects (for example, fuel reduction, habitat improvement for sage-grouse, and other sagebrush species) and facilitate science that further quantifies ecological effects of pinyon-juniper encroachment on sage-grouse populations and sagebrush ecosystem processes. Hence, we mapped pinyon-juniper (referred to as conifers for actual mapping) at a 1 × 1-meter (m) high resolution across the entire range of previously mapped sage-grouse habitat in Nevada and northeastern California.

We used digital orthophoto quad tiles from National Agriculture Imagery Program (2010, 2013) as base imagery, and then classified conifers using automated feature extraction methodology with the program Feature Analyst™. This method relies on machine learning algorithms that extract features from imagery based on their spectral and spatial signatures. We classified conifers in 6,230 tiles and then tested for errors of omission and commission using confusion matrices. Accuracy ranged from 79.1 to 96.8, with an overall accuracy of 84.3 percent across all mapped areas. An estimated accuracy coefficient (kappa) indicated substantial to nearly perfect agreement, which varied across mapped areas. For this mapping process across the entire mapping extent, four sets of products are available at https://doi.org/10.5066/F7348HVC, including (1) a shapefile representing accuracy results linked

to mapping subunits; (2) binary rasters representing conifer presence or absence at a 1 × 1 m resolution; (3) a 30 × 30 m resolution raster representing percentages of conifer canopy cover within each cell from 0 to 100; and (4) 1 × 1 m resolution canopy cover classification rasters derived from a 50-m-radius moving window analysis. The latter two products can be reclassified in a geographic information system (GIS) into user-specified bins to meet different objectives, which include approximations for phases of encroachment. These products complement, and in some cases improve upon, existing conifer maps in the Western United States, and will help facilitate sage-grouse habitat management and sagebrush ecosystem restoration.

Introduction

The iconic "sagebrush sea" that characterizes the Great Basin of the Western United States is larger than 75 percent of countries worldwide (Coates, Ricca, and others, 2016) and provides habitat for several at-risk sagebrush-obligate species (Wisdom and others, 2005; Homer and others, 2009; Knick and others, 2013). Sagebrush ecosystems also support outdoor recreation valued at $1 billion annually (Bureau of Land Management and U.S. Forest Service, 2014) and cattle grazing, valued as high as $60 billion in a single year (U.S. Department of Agriculture Economic Research Service, 2016). It is also one of the most endangered ecosystems in the United States (Noss and others, 1995), as the range of sagebrush has contracted by more than 50 percent since European settlement. The remaining range is subjected to continual fragmentation, largely from anthropogenic-related disturbances (Knick and others, 2003; Schroeder and others, 2004). Accordingly, sagebrush ecosystems are at the center of national conservation strategy (U.S. Department of Interior, 2015).

Conifers such as pinyon (*Pinus monophylla*) and juniper (*Juniperus osteosperma, J. occidentalis*; hereinafter, "pinyon-juniper") are a native component of the sagebrush ecosystems in the Great Basin. However, the distribution and abundance of pinyon-juniper has greatly expanded following European settlement (Miller and Tausch, 2001), with as much as a 10-fold increase owing to a variety of factors, including changes in climate (Soulé and others, 2004; Romme and others, 2009), land use (Miller and Wigand, 1994; Miller and Rose, 1999; Romme and others, 2009), and fire regimes (Burkhardt and Tisdale, 1976; Miller and Rose, 1999; Miller and others, 2000; Soulé and others, 2004). Accordingly, encroachment of pinyon-juniper is a major factor contributing to the fragmentation and loss of sagebrush ecosystems and the processes that maintain them in an intact state (Davies and others, 2011; Miller and others, 2011; Knick and others, 2013). For example, dominance of sagebrush and perennial grasses, which contribute strongly to sagebrush ecosystem resilience to disturbance and resistance to invasion (Chambers and others, 2014), decreases as cover of pinyon-juniper increases (Miller and others, 2005). This relationship can be categorized into three distinct phases of encroachment (Miller and others, 2005), where in the simplest terms, sagebrush is dominant over pinyon-juniper in phase 1 (> 0 and ≤ 10 percent pinyon-juniper canopy cover), sagebrush and pinyon-juniper are co-dominant in phase 2 (> 10 and ≤ 30 percent pinyon-juniper canopy cover), and pinyon-juniper is dominant and has replaced sagebrush in phase 3 (> 30 percent pinyon-juniper canopy cover).

The loss of shrub and herbaceous understory components with increasing phase of encroachment diminishes forage and cover for constituent wildlife (Connelly and others, 2000; Miller and others, 2000, 2011; Beck and others, 2012) and reduces available forage for cattle (Bedell and Borman, 1997; Soulé and Knapp, 1999; Twidwell and others, 2013). Pinyon-juniper encroachment also reduces streamflow (Huxman and others, 2005; Kormos and others, 2017), depletes soil water availability (Huxman and others, 2005; Roundy and others, 2014; Kormos and others, 2017), and increases bare earth contiguity that promotes runoff and subsequent soil erosion (Davenport and others, 1998; Pierson and others, 2010). Perhaps most importantly, pinyon-juniper contributes to the severe wildfires that have escalated substantially since the 1980s (Running, 2006). The spread of pinyon-juniper into low-elevation sagebrush ecosystems combined with infill of pinyon-juniper into new woodlands introduces woody biomass that fuels more intense wildfires (Running, 2006; Bradley and Fleishman, 2008; Romme and others, 2009). Burned pinyon-juniper stands are often replaced by invasive annual grasses that have a positive feedback cycle with wildfire, thereby increasing fire extent and frequency and spreading fire into sagebrush that would otherwise be much less likely to burn (Tausch and others, 1999, 2009; Romme and others, 2009; Davies, 2011; Balch and others, 2013). Because of the multitude of economic and ecological effects from sagebrush loss, pinyon-juniper encroachment is now a primary challenge facing land managers in the Western United States (Barger and others, 2009; Davies and others, 2011; Weltz and others, 2014).

A major impetus for sagebrush restoration efforts is the conservation of greater sage-grouse (*Centrocercus urophasianus*; hereinafter, "sage-grouse"), which is a sagebrush-obligate species that has declined concomitantly with the loss of sagebrush (Schroeder and others, 2004; Connelly and others, 2011) and has been considered for listing multiple times under the Endangered Species Act of 1973 (U.S. Fish and Wildlife Service, 2015). Sage-grouse act as an indicator-species for the health of sagebrush ecosystems because they require expanses of undisturbed sagebrush throughout the year to fulfill their life history requirements (Rowland and others, 2006; Hanser and Knick, 2011). Pinyon-juniper encroachment, in conjunction with wildfire, is a primary threat to sage-grouse populations in many parts of the Great Basin (U.S. Fish and Wildlife Service, 2013, 2015). Pinyon-juniper replaces and subsequently fragments sagebrush used for nesting cover and forage (Connelly and others, 2004; Crawford and others, 2004; Doherty and others, 2008; Knick and Connelly, 2011) and can increase predation risk from visually acute predators such as ravens and raptors (Howe and others, 2014). Sage-grouse strongly avoid pinyon-juniper (Doherty and others, 2008; Atamian and others, 2010; Casazza and others, 2011; Knick and others, 2013), which can function as impediments to gene flow among populations (Oyler-McCance and others, 2005, 2014). Furthermore, pinyon-juniper cover as little as 2–4 percent can negatively affect lek persistence (Baruch-Mordo and others, 2013) and sage-grouse survival (Coates and others, 2017; Prochazka and others, 2017). Effects on survival can be especially important when scattered trees occur in highly productive cool and moist sagebrush habitats that can become ecological traps for sage-grouse (Coates and others, 2017). Moreover, recent studies have demonstrated how sage-grouse can respond positively to pinyon-juniper removal through improved nest and brood survival (Sanford and others, 2017; Severson and others, 2017).

The consequences of pinyon-juniper expansion on sage-grouse population decline are regional in scope, requiring cooperative conservation efforts by Federal and State agencies that total millions of dollars (Sanford and others, 2017). The removal of pinyon-juniper is becoming a principal component of conservation plans (Peters and Cobb, 2008; U.S. Fish and Wildlife Service, 2013; Miller and others, 2014; Nevada Department of Wildlife, 2014; U.S. Department of Agriculture Natural Resources Conservation Service, 2014; Duvall and others, 2017; Miller and others, 2017; Severson and others, 2017). As agencies implement restoration efforts over thousands of hectares (Miller and others, 2017), there is an immediate need for high-resolution conifer data over regional spatial extents to optimize targeted removal efforts (Connelly and others, 2004; Homer and others, 2009; Bradley, 2010; Falkowski and others, 2017). The resolution of such spatial data must be fine enough to precisely determine conifer distribution and accurately classify the concentration of conifers even at low densities. This is essential to the success of restoration efforts, as even a small percentage of canopy cover is detrimental to sage-grouse populations (Baruch-Mordo and others, 2013; Coates and others, 2017). Additionally, the removal of low density (phases 1 and 2) pinyon-juniper is more effective at restoring intact sagebrush community structure, due in part to relatively intact understory community structure and soil characteristics (Miller and others, 2008). Moreover, spatially explicit conifer data are used in models underlying incentive-based programs that prioritize areas for conifer treatment based on estimated benefits to sage-grouse (U.S. Fish and Wildlife Service, 2013; State of Nevada Conservation Credit System, 2017). Accurate mapping of contemporary conifer distribution in addition to continuous estimates of canopy cover or categorized estimates of phases of encroachment can allow managers to better direct resources to areas that yield maximum improvement to sage-grouse populations or other sagebrush ecosystem services.

Remote sensing offers a more efficient and less expensive approach than land-based forest and rangeland inventory methods for identifying conifers and classifying canopy cover across large spatial extents (Homer and others, 2009; Davies and others, 2010; Falkowski and others, 2017) because the latter efforts often require extensive human resources, time, and protocol standardization. However, the customary classification products derived from satellite imagery at large spatial extents generally target a few limited classes (Lang and Langanke, 2005) and do not have the spatial resolution necessary to target areas for pinyon-juniper removal based on distributions of single or sparsely scattered trees (Davies and others, 2010; Falkowski and Evans, 2012). For example, the resolution of Landsat-based mapping products (30 × 30 m, or 900 square meters [m^2]) can be too coarse to identify the early stages of pinyon-juniper encroachment (for example, as low as 10 percent canopy cover) that often constitute the best candidate areas for pinyon-juniper removal (Miller and others, 2008; Baruch-Mordo and others, 2013; Coates and others, 2017). Additionally, Landsat can overestimate stands of high density conifer because the cell size of the imagery often exceeds the diameter of individual trees on the landscape (fig. 1).

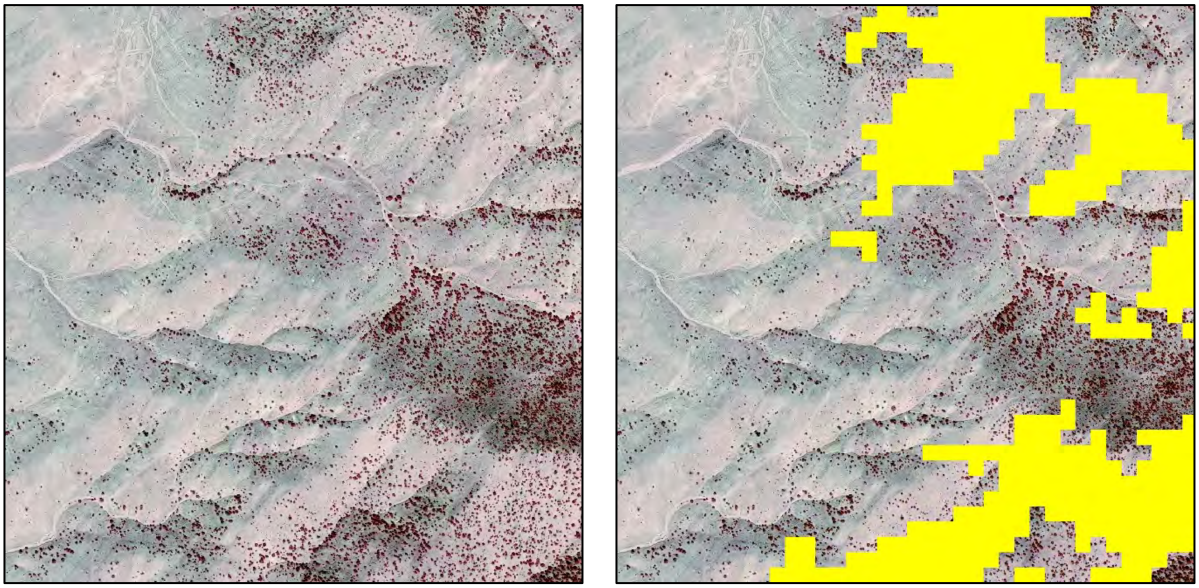


Figure 1. Pinyon-juniper in false-color, 1 × 1 m resolution National Agricultural Imagery Program (left) and Landsat-derived 30 × 30 m resolution pinyon-juniper class overlay (right).

Recent advances in remote sensing, computing power, and feature recognition technologies such as object-based image analysis (OBIA) can be applied readily to very high spatial resolution (VHSR) imagery (< 2 × 2 m) to identify individual conifers on the landscape (Davies and others, 2010; Falkowski and Evans, 2012; Mishra and Crews, 2014; Falkowski and others, 2017). OBIA exploits VHSR imagery by segmenting cells into image-objects based on their spectral, spatial, and structural properties, and then classifies these image-objects to extract features of interest (Burnett and Blaschke, 2003; Hay and others, 2003; Benz and others, 2004; Hay and Castilla, 2006; Alpin and Smith, 2008). Segmentation facilitates accurate conifer delineation from VHSR imagery as conifer canopies can be as wide as 10 m (Falkowski and others, 2017) and encompass multiple cells with variable properties. OBIA can also implement supervised and hierarchical learning to train algorithms and hone accuracy of image object outputs by iteratively correcting operator-identified artifacts of over- or under-classification. Classification of conifer features using OBIA on VHSR imagery has been shown to reliably identify forest canopy in relatively small test scenarios (Davies and others, 2010; Madsen and others, 2011; Falkowski and Evans, 2012; Hulet and others, 2013; Roundy, 2015).

We applied OBIA across all previously mapped sage-grouse habitat in Nevada and northeastern California (Coates, Casazza, Ricca, and others, 2016; Coates, Casazza, Brussee, and others, 2016) to identify individual conifers statewide and provide land managers with practical data that can be used in restoration efforts. Although pinyon-juniper comprise the majority of conifers and conifer-like functional types in our mapping extent, we use the term conifer when referring to map output because we could not distinguish among different conifer species. We mapped conifers at a resolution of 1 × 1 m using National Agriculture Imagery Program (NAIP; U.S. Department of Agriculture, 2014) imagery collected in 2010 and 2013 as our reference data and the Feature Analyst™ toolbox (Overwatch

Systems, Ltd., Sterling, Virginia) for Esri® ArcGIS™ Desktop (Esri, 2013, Release 10.2, Redlands, California). Feature Analyst™ is an accelerated feature extraction (AFE) method that semi-automates the extraction of target features using a machine learning algorithm trained to delineate image-objects based on the spectral and spatial signatures of defined cell neighborhoods (Opitz and Blundell, 2008). AFE outperforms pixel-based methods (Riggan and Weih, 2009; Weih and Riggan, 2010) and is recognized as one of the most accurate OBIA methods available (Opitz and Blundell, 2008; Tsai and others, 2011). We identified examples of conifer image objects to create 1 × 1 m resolution binary conifer rasters (gridded spatial data that represent conifer presence as cells with values of one) for each sage-grouse population management unit (PMU; Nevada Department of Wildlife, 2014) across the full mapping extent, and conducted extensive analyses of omission and commission to provide estimates of mapping accuracy by PMU. We then scaled the 1 × 1 m resolution data into unsmoothed (30 × 30 m) and 50-m radius moving-window smoothed (1 × 1 m) estimates of percent canopy cover to facilitate identification of pinyon-juniper encroachment phases at resolutions sought by land managers. We offer the 30 × 30 m product for seamless integration into current geospatial applications that use standard 30 × 30 m resolution products, while the 1 × 1 m product allows users to estimate conifer cover with higher accuracy than currently available. These products provide highly accurate depictions of pinyon-juniper distribution and canopy cover which inform sage-grouse habitat suitability and population response models (Coates, Casazza, Ricca, and others, 2016; Coates and others, 2017; Prochazka and others, 2017), and can provide land managers with actionable metrics for assessing the efficacy of pinyon-juniper removal projects.

Study Methods

Study Area Mapping and Selection

Conifer mapping was conducted for all 61 Nevada Department of Wildlife (NDOW) sage-grouse PMUs (fig. 2). PMUs are population-specific spatial boundaries primarily generated from sage-grouse lek distributions, but they also incorporate the habitat availability and environmental factors that influence each sage-grouse population (Nevada Department of Wildlife Sage Grouse Conservation Plan, 2001, appendix C). We selected PMUs because they represent the geographic extent of any NDOW management prescriptions and coincide with sage-grouse habitat models that are used to prioritize conservation areas (Coates, Casazza, Ricca, and others, 2016; Coates Casazza, Brussee, and others, 2016). We buffered the extent of the PMUs by 10 kilometers (km) to prevent inaccurate moving window (or neighborhood) calculations within the study area along boundaries where "No Data" values would occur (fig. 2). We selected this buffer size because it exceeds the radius of any neighborhood calculations land managers might apply, as sage-grouse typically are not using habitat more than 8 km from lek locations (Holloran and Anderson, 2005; Coates and others, 2013).

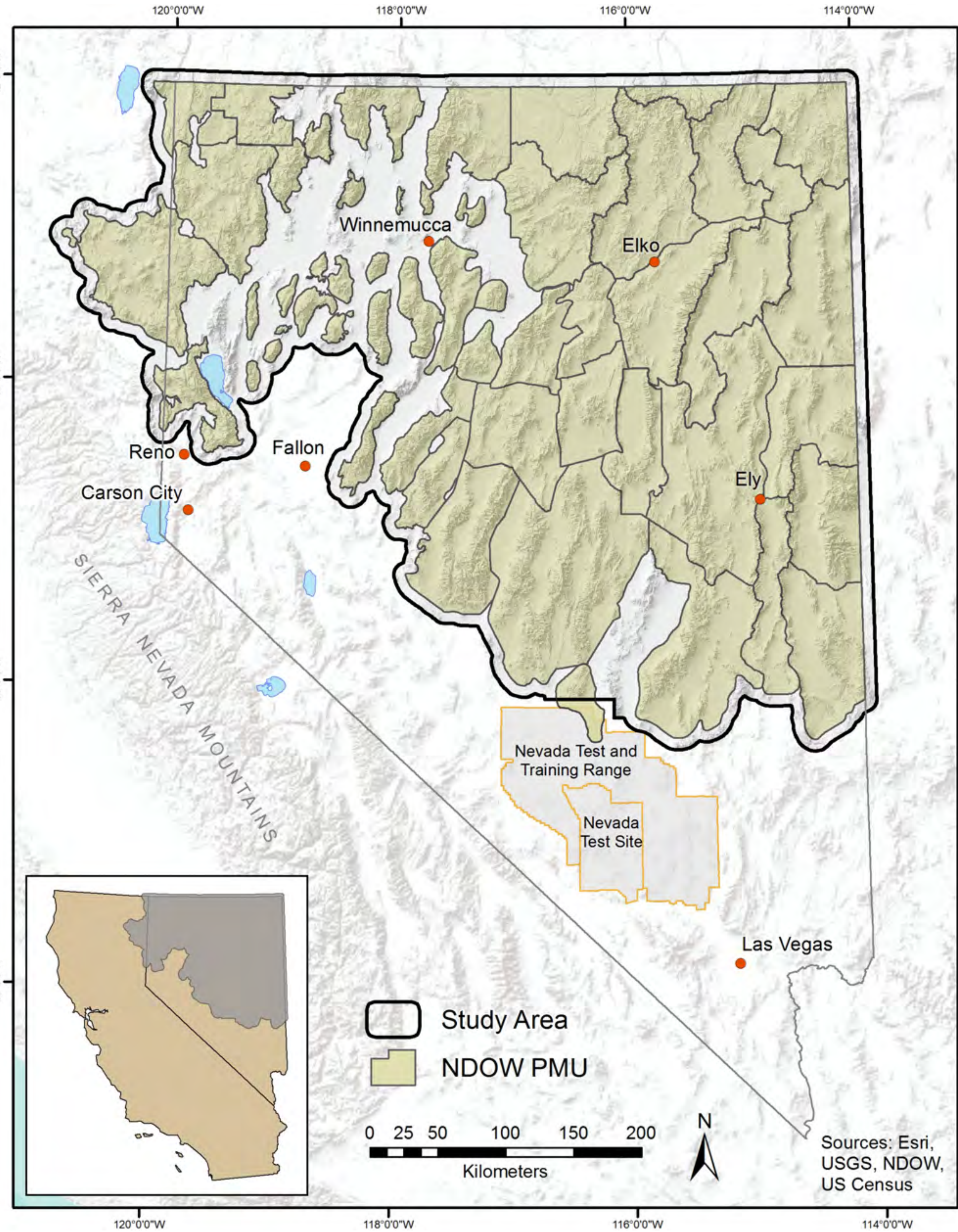


Figure 2. Map showing study area extent of mapped conifers using automated feature extraction methods within sage-grouse habitat in Nevada and California.

Feature Extraction

We used the NAIP digital orthophoto quarter quads (DOQQs) because they are freely available, orthorectified, VHSR (1 × 1 m) products that comprise four spectral bands (three visible-light bands [RGB] and a near-infrared band). These features are for identifying vegetation and distinguishing among vegetation types, including conifers. Our study extent included 6,230 DOQQs from Nevada and California (fig. 3), which also includes small areas along the state borders of Oregon, Idaho and Utah that fell within the buffered PMU boundary. A small section of our study area along the southern boundary was truncated by the Nevada Military Test and Training Range where the NAIP imagery was unavailable or redacted. We analyzed PMUs on a tile-by-tile basis by intersecting polygon boundaries of the DOQQs with the PMUs because inconsistencies among DOQQs such as varying image quality, changes in lighting, inconsistent spectral values, shadows, parallax, and processing artifacts required independent analysis of each tile for greatest classification accuracy. Although mosaicking tiles into continuous surfaces for each PMU would allow for color correction, the extent of each PMU is so large that a VHSR mosaic of associated DOQQs would be very time consuming and computationally intensive to analyze by AFE, as well as nearly impossible to inspect for classification errors. Due to these processing limitations, we further divided larger PMUs such as Monitor, Quinn, and Buffalo-Skedaddle into smaller, more manageable zones. Zone boundaries followed DOQQ boundary polygons and were selected in low to non-conifer areas to minimize the potential for seamlines in classifications.

We reviewed each tile initially for the presence of conifers and processed tiles individually that consisted of conifers using the Feature Analyst™ Supervised Learning Wizard. This tool applies a supervised learning algorithm that extracts features meeting the spectral and contextual specifications provided by the user via a set of training polygons. We digitized a representative sample of conifer image objects selected across the entire tile to create a polygon training set (fig. 3a). Conifers were identified using traditional False Color settings, which display vegetation as red. We distinguished conifers from other vegetation based on the hue of red and identification was verified in Google Earth™ (version 7.1.2.2041 2013; fig. 3a). We digitized clearly identifiable individual conifers for the training polygons to ensure the classification of isolated trees in low canopy density areas and used the spectral properties of the cells under false-color settings to delineate the conifer crown. This process trained the OBIA algorithm to distinguish trees from shadows and other vegetation types, preventing misclassification. Each digitized image object consisted of at least three cells, as we assumed tree heights of digitized trees were not less than 3 m. The number of samples per tile varied according to image quality and color variation, but always consisted of a minimum of five training polygons (fig. 3a).

We then used the training set as the input for Feature Analyst™'s Supervised Learning Wizard to generate conifer features from the four-band NAIP image (fig. 3b). In the Wizard, we specified parameters that best represented trees in the supervised machine learning algorithm. We defined our search neighborhoods using the "Natural Feature" feature selector with the "Bullseye 3" parameter over a 5 × 5 m moving window to define the spatial and spectral context used by the algorithm to extract features (fig. 3b). "Natural Shape" discouraged the algorithm from using hard lines to generate image objects. The Bullseye search window reduced processing time by reducing the number of cells supplied to the learning algorithm while still representing the neighborhood.

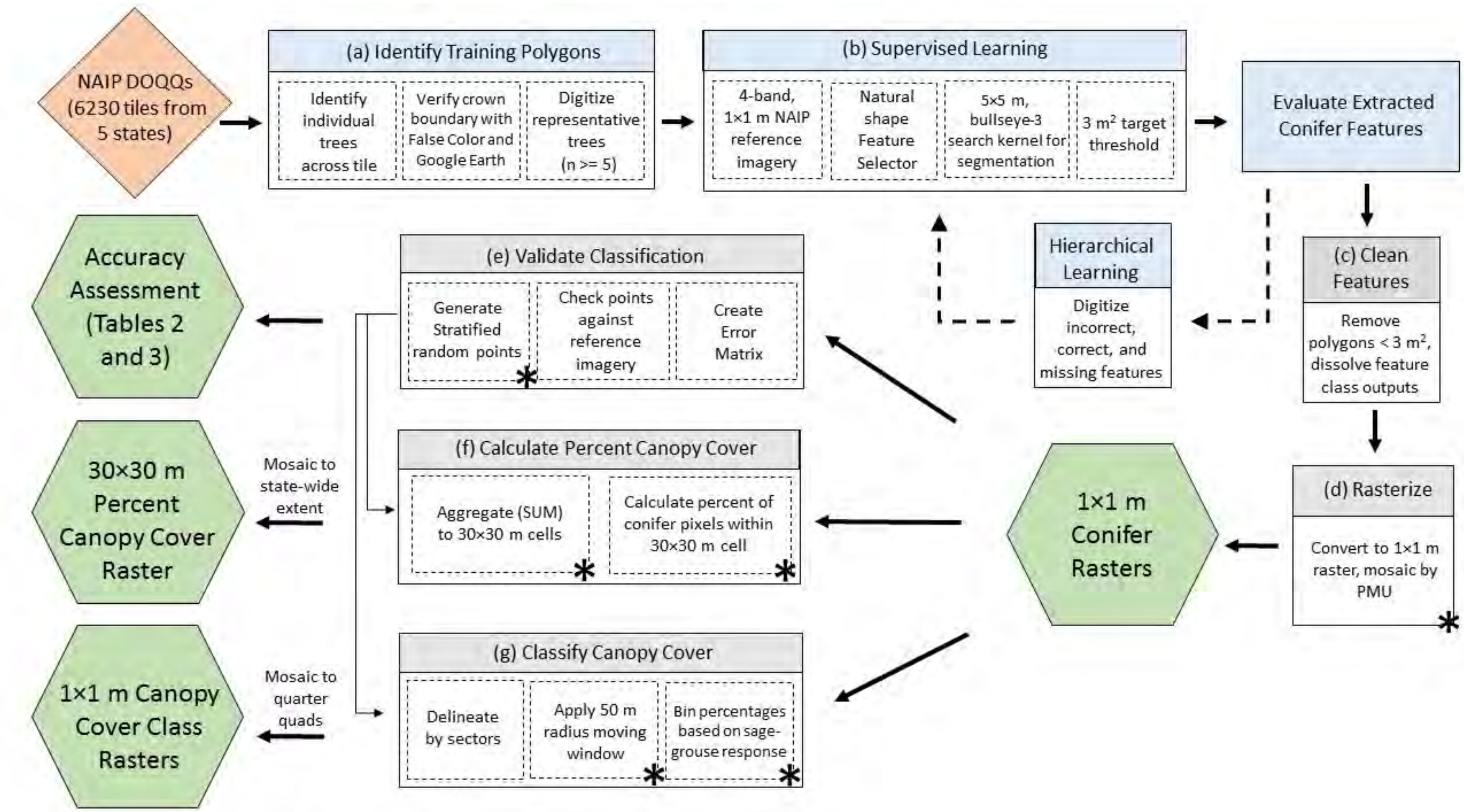


Figure 3. Schematic showing conceptual model of conifer classification framework using automated feature extraction methods within greater sage-grouse habitats in Nevada and California. Input is represented as orange diamond and green hexagon identifies products. Blue and gray boxes represent steps conducted in Feature Analyst™ and a GIS software, respectively. Starred items (*) denote iterated geoprocessing steps.

We specified a "pattern width" of 5 m to match the Bullseye moving window, and we chose 5 m in both instances because this width was larger than our minimum mapping unit, allowing the algorithm to discern features based on collective spectral qualities while still small enough to extract individual trees. Additionally, it allowed us to exclude smaller vegetation with similar spectral signatures and reduce the chance for errors of commission. Detected features less than 3 m^2 were aggregated (fig. 3b). These parameters were determined to best classify trees after several rounds of tests.

We checked output conifer features for accuracy against the NAIP reference imagery. Typically, the initial results would be over- or under-classified. If the results were under-classified, more training polygons were added to the initial set and a new supervised classification was performed to replace the initial output. In some cases where a single learning algorithm could not be trained to recognize all conifer features (that is, extremely dense stands), multiple algorithms were run on the same tile to target the variety of feature types and these outputs were merged together. If the results were over-classified, the analyst would proceed with the "Hierarchical Learning" process in Feature Analyst™ (fig. 3). First, we digitized incorrect features for removal using the "Begin Removing Clutter Tool." We provided removal polygon samples of all possible misclassifications such as shadows, riparian vegetation, and other non-conifer features. The correct output features were then identified to retrain the OBIA algorithm. Finally, we digitized features that were missed by the previous supervised learning run and added to the training set using the "Begin Adding Missed Features Tool." The incorrect, correct, and missed features were all incorporated into a hierarchical supervised classification performed on the previous OBIA output. This hierarchical classification continued until misclassification errors were minimized based on visual comparison of feature outputs to the NAIP reference imagery.

We carried out several post-processing steps (fig. 3c) on output feature layers for each tile to further improve results. First, features were run through additional geoprocessing tools to dissolve overlapping features, repair polygon geometry, and remove features less than 3 m^2. Any large misclassifications that occurred due to spectral overlap (algae in standing water, irrigated agricultural fields, wet meadows, riparian areas, or patches of other non-conifer vegetation) were removed using custom polygon masks. We then converted the clean shapefiles for each tile to 2-bit, binary VHSR rasters (1 × 1 m; fig. 3d) and reviewed for obvious errors of omission and commission. We also checked against neighboring tiles for acute seamlines, which were signs of classification disagreement resulting from tile-based analysis. If classification agreement was not satisfactory, then we re-analyzed tiles. Clean rasters for each zone or PMU were mosaicked in ERDAS Imagine (2013, Leica Geosystems, Atlanta, Georgia; fig. 3d) using the "Automatic Most Nadir Seam" setting, which overlaps areas where the distance to the center point of each image is equal and minimizes seamlines.

Canopy Cover Study Methods

After validation (see section, "Conifer Mapping Results"), final mosaics were used to calculate high resolution estimates of percent canopy cover for the entire study area in two distinct ways. In the first method, we simply aggregated by summing the number of 1 × 1 m conifer cells within a 30 × 30 m cell and divided by its area, which yielded a floating point raster of percent canopy cover per 30 × 30 m cell (fig. 3f). This was converted to whole numbers of percent canopy cover ranging from 0 to 100. For the second method, the large file sizes of the VHSR PMU/zone mosaics made it necessary to perform the calculation on smaller extents (fig. 3g). Hence, we divided the study area into 37 grid sectors of equal extent and mosaicked PMUs that intersected each sector. We then calculated percent canopy cover by summing all cell values within a 50-m radius neighborhood (equivalent to 7,845 m^2) and dividing by the total number of cells within that neighborhood. To accommodate land managers, we reclassified the cells according to multiple intervals of percent canopy cover (table 1). Canopy cover intervals were based on known biological significance to sage-grouse (Baruch-Mordo and others, 2013; Coates and others, 2017). Sage-grouse avoid canopy cover as low as 4 percent (Baruch-Mordo and others, 2013; Coates and others, 2017), therefore we maintained individual intervals for each percentage less than 10 percent.

To assess the accuracy of OBIA conifer classification, we constructed a confusion matrix (Congalton and Green, 2009) for each PMU. We first generated stratified random points within our 1-m conifer and non-conifer classes and compared our classification at those locations against NAIP reference imagery (fig. 3e). We standardized the number of points by sampling 100 points per the average classified area (km^2) of the PMUs. We then divided the area of each PMU (km^2) by this km^2-per-point value to weight the number of random points generated for each PMU by its area, with a required minimum of 25 points generated for each PMU. Each random point was visually inspected for errors of omission (for example, failing to identify a conifer that occurred) and commission (for example, incorrectly classifying a non-conifer as a conifer), and the results entered in the confusion matrix (fig. 3e). We calculated the overall accuracy of conifer and non-conifer classification in each PMU, which identifies the percent of correct classifications from the total cases examined. To investigate bias in the OBIA towards errors of commission or omission, we also calculated the user's and producer's accuracy, respectively. The user's accuracy represents errors of commission, or the inclusion of pixels that are not the specified class, while the producer's accuracy reflects errors of omission, or the exclusion of pixels in the correct class. The user's accuracy evaluates the reliability of the output conifer class by determining the percentage of cases correctly attributed to each class and the producer's accuracy assesses the performance of the classification algorithm by identifying the percent detection of all cases in each class. The values in the confusion matrices were used to perform an estimated accuracy coefficient (kappa) analysis, which is generally accepted as the best means of assessing the accuracy of image processing products (Congalton and Green, 2009). The kappa analysis generates the kappa coefficient (K_{hat}), which represents the percent accuracy adjusted for correct classification due to random chance. A positive K_{hat} indicates the results in the confusion matrix are better than a random result (Jensen, 1996). We generated K_{hat} statistics for each PMU. We used the Landis and Koch (1977) interpretation of kappa, where K_{hat} greater than 60 percent indicate substantial agreement between classification and truth, and those greater than 80 percent are almost perfect.

Table 1. Canopy cover class intervals for mapped conifers at the 1-meter resolution using intensive automated feature extraction methods within greater sage-grouse habitat of Nevada and California.

[Percentages were based on 50-meter radius neighborhood (7,845 square meters).]

Class	Percent canopy cover
0	0
1	> 0 to 1
2	>1 to 2
3	>2 to 3
4	>3 to 4
5	>4 to 5
6	>5 to 6
7	>6 to 7
8	>7 to 8
9	>8 to 9
10	>9 to 10
11	>10 to 15
12	>15 to 20
13	>20 to 25
14	>25 to 30
15	>30 to 35
16	>35 to 40
17	>40 to 45
18	>45 to 50
19	> 50

Conifer Mapping Results

We provide four sets of conifer classification products for the full extent of our study area within the State of Nevada (available for free download with accompanying metadata at https://doi.org/10.5066/F7348HVC): (1) a shapefile representing confusion matrix results linked to its respective PMU or zone; (2) binary rasters identifying conifer presence or absence at a 1 × 1 m resolution, available by PMU; (3) a 30 × 30 m resolution raster representing percentages of conifer canopy cover within each cell (fig. 4); and (4) 50-m radius moving window canopy cover class rasters at a 1 × 1 m resolution, available in quadrants. Importantly, the latter two products can be reclassified in a GIS into user-specified bins to meet different objectives, which include approximations for phases of pinyon-juniper encroachment into sagebrush ecosystems. These products complement, and in some cases improve upon, existing conifer maps in the Western United States, and will help facilitate sage-grouse habitat management and restoration of sagebrush ecosystems.

We reported accuracy assessments for each PMU (table 2; fig. 5) and summarized accuracy results across all PMUs (table 3). Three of the PMUs do not have accuracy assessments because we did not detect any conifers within the PMU boundaries (table 2; fig. 5). Further detail of the error matrices for the 1 × 1 m resolution conifer classification by PMU, as well as user's accuracy, producer's accuracy, overall accuracy, and K_{hat} for each PMU is reported in appendix A and the embedded metadata of each mosaic raster file (https://doi.org/10.5066/F7348HVC). User's and producer's accuracies ranged from 60 to 95.16 percent (fig. 6, left) and 71 to 100 percent (fig. 6, right), respectively. On average, conifer classification had higher incidence of errors of commission reported as conifer user's accuracy (76.07 percent; standard deviation [SD] = 8.50 percent; table 3) than non-conifer user's accuracy (97.11 percent; SD = 3.10 percent; table 3). Accordingly, errors of omission were more common for non-conifer classification (producer's accuracy = 80.63 percent; SD = 5.69 percent; table 3) compared to conifer classification (96.51 percent; SD = 3.59; table 3). The overall accuracies of all classes for individual PMUs ranged from 79 to 97 percent (fig. 5), with a mean of 86.38 percent (SD = 4.21 percent; table 3). Mean adjusted accuracy showed that there was substantial agreement between classes and reference imagery (K_{hat} = 73.17 percent; SD = 8.50 percent; table 3). Twenty-five percent of the PMUs had almost perfect classification ($K_{hat} \geq 80$ percent) and only Zone 2 of Monitor and Limbo had an adjusted accuracy that rated lower than substantial agreement ($K_{hat} \leq 60$ percent; table 2).

Table 2. Accuracy results of mapping conifers at the 1-meter resolution by population management unit using intensive automated feature extraction methods within greater sage-grouse habitat of Nevada and California.

[$\boldsymbol{K_{hat}}$, estimated accuracy coefficient. N/A, population management units where conifers were not detected]

Population management unit	Conifer user's accuracy (percent)	Non-conifer user's accuracy (percent)	Conifer producer's accuracy (percent)	Non-conifer producer's accuracy (percent)	Overall accuracy (percent)	K_{hat} (percent)
Battle Mountain	68.00	100.00	100.00	75.76	84.00	68.00
Black Rock	68.00	100.00	100.00	75.76	84.00	68.00
Buffalo-Skedaddle	70.78	92.19	90.06	75.93	81.49	62.97
Butte/ Buck/White Pine	82.58	91.57	90.74	84.02	87.08	74.16
Clan Alpine	78.45	99.14	98.91	82.14	88.79	77.59
Cortez	70.00	98.33	97.67	76.62	84.17	68.33
Desatoya	95.16	98.39	98.33	95.31	96.77	93.55
Desert	68.00	100.00	100.00	75.76	84.00	68.00
Diamond	80.41	95.88	95.12	83.04	88.14	76.29
East Valley	79.17	93.52	92.43	81.78	86.34	72.69
East Range	63.77	97.10	95.65	72.83	80.43	60.87
Eden Valley	N/A	N/A	N/A	N/A	N/A	N/A
Eugenes	68.00	96.00	94.44	75.00	82.00	64.00
Fish Creek	65.71	100.00	100.00	74.47	82.86	65.71
Gollaher	73.80	94.65	93.24	78.32	84.22	68.45
Humboldt	89.74	100.00	100.00	90.70	94.87	89.74
Islands	69.62	100.00	100.00	76.70	84.81	69.62
Jackson	70.00	96.67	95.45	76.32	83.33	66.67
Kawich	81.03	93.10	92.16	83.08	87.07	74.14
Limbo	60.00	100.00	100.00	71.43	80.00	60.00
Lincoln	78.10	89.54	88.19	80.35	83.82	67.65
Lone Willow	64.00	100.00	100.00	73.53	82.00	64.00
Majuba 1 and 2	84.62	100.00	100.00	86.67	92.31	84.62
Majuba 3 and 4	69.44	100.00	100.00	76.60	84.72	69.44
Massacre	80.61	98.98	98.75	83.62	89.80	79.59
Nightengale	76.00	100.00	100.00	80.65	88.00	76.00
North Fork	82.43	100.00	100.00	85.06	91.22	82.43
O'Neil Basin	63.89	100.00	100.00	73.47	81.94	63.89
Pine Forest	80.00	100.00	100.00	83.33	90.00	80.00
Reese River	82.03	94.01	93.19	83.95	88.02	76.04
Ruby Valley	66.67	96.11	94.49	74.25	81.39	62.78
Sahwave 1 and 2	88.00	96.00	95.65	88.89	83.80	84.00

Population management unit	Conifer user's accuracy (percent)	Non-conifer user's accuracy (percent)	Conifer producer's accuracy (percent)	Non-conifer producer's accuracy (percent)	Overall accuracy (percent)	K_{hat} (percent)
Santa Rosa	N/A	N/A	N/A	N/A	N/A	N/A
Schell/Antelope	69.95	97.95	96.75	76.47	83.80	67.61
Sheldon	84.48	100.00	100.00	86.57	92.24	84.48
Shoshone	66.67	98.33	97.56	74.68	82.50	65.00
Slumbering Hills	N/A	N/A	N/A	N/A	N/A	N/A
Snake	75.71	97.14	96.36	80.00	86.43	72.86
Sonoma	83.64	100.00	100.00	85.94	91.82	83.64
South Fork	67.46	98.22	97.44	75.11	82.84	65.68
Steptoe Cave	83.78	90.09	89.42	84.75	86.94	73.87
Stillwater	75.51	91.84	90.24	78.95	83.67	67.35
Three Bar	86.60	95.88	95.45	87.74	91.24	82.47
Toiyabe	72.67	98.67	98.20	78.31	85.67	71.33
Trinity 1 and 2	92.00	96.00	95.83	92.31	94.00	88.00
Tuscarora	84.00	100.00	100.00	86.21	92.00	84.00
Virginia-Pahrah	78.09	97.75	97.20	81.69	87.92	75.84
Vya	72.32	93.22	91.43	77.10	82.77	65.54
Zone 1 (Monitor)	75.47	90.57	88.89	78.69	83.02	66.04
Zone 2 (Monitor)	61.96	96.32	94.39	71.69	79.14	58.28
Zone 3 (Monitor)	73.83	97.99	97.35	78.92	85.91	71.81
Zone 4 (Monitor and Quinn)	75.47	100.00	100.00	80.30	87.74	75.47
Zone 5 (Quinn)	84.97	99.35	99.24	86.86	92.16	84.31
Zone 6 (Quinn)	87.94	97.87	97.64	89.03	92.91	85.82
Zone 7 (Quinn)	88.00	92.00	91.67	88.46	90.00	80.00
Spring-Snake Valley	72.92	96.35	95.24	78.06	84.64	69.27

Table 3. Summarized results of mapping conifers at the 1-meter resolution across all population management units using intensive accelerated feature extraction methods within greater sage-grouse habitat of Nevada and California.

[Means are shown with 1 standard deviation. K_{hat}: Estimated accuracy coefficient.]

	Conifer user's accuracy (percent)	Non-conifer user's accuracy (percent)	Conifer producer's accuracy (percent)	Non-conifer producer's accuracy (percent)	Overall accuracy (percent)	K_{hat} (percent)
Mean	76.07 ± 8.50	97.11 ± 3.10	96.51 ± 3.59	80.63 ± 5.70	86.38 ± 4.21	73.17 ± 8.50
Minimum	60	89.54	88.19	71.43	79.14	58.28
Maximum	95.16	100	100	95.31	96.77	93.55

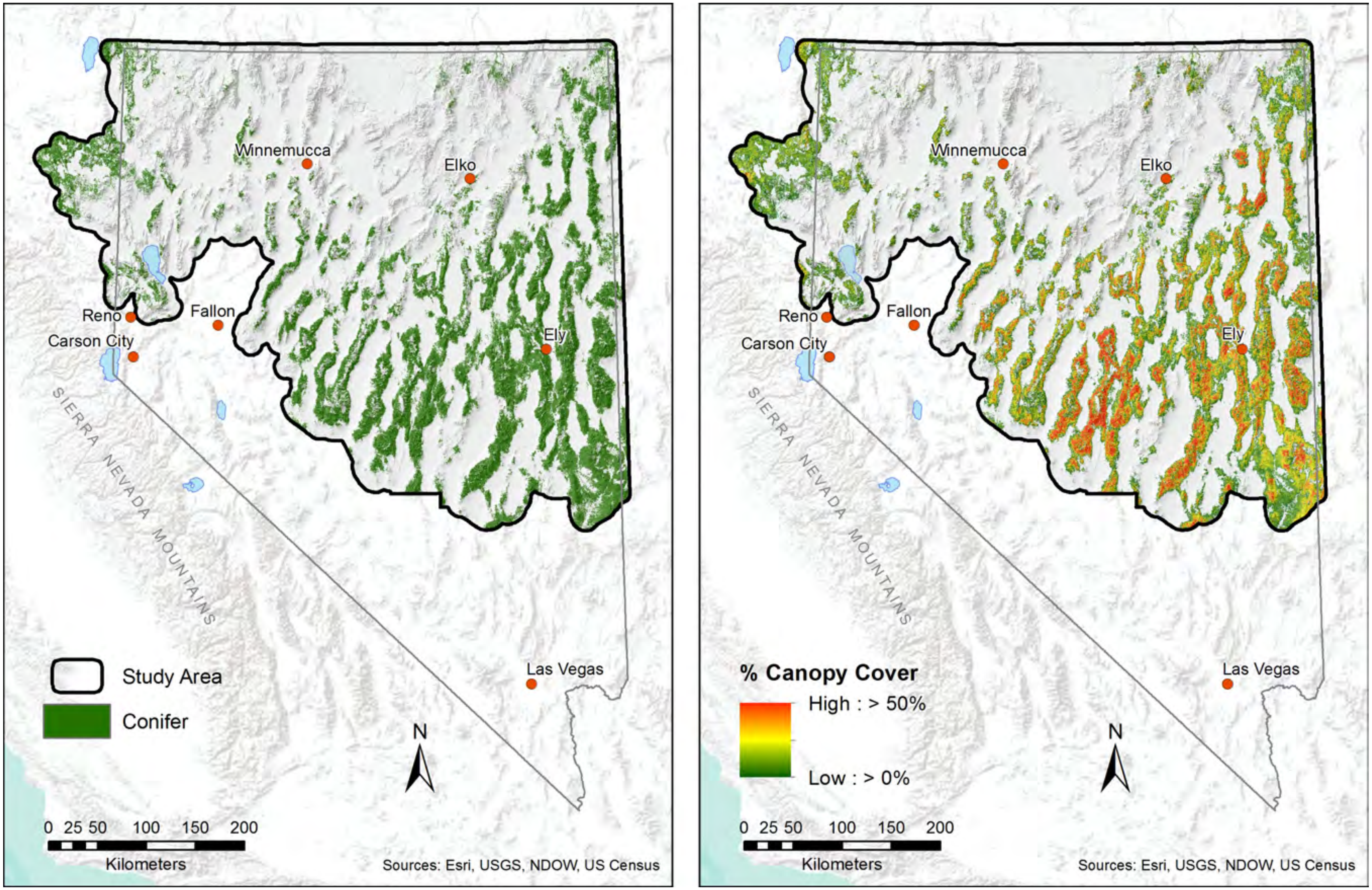
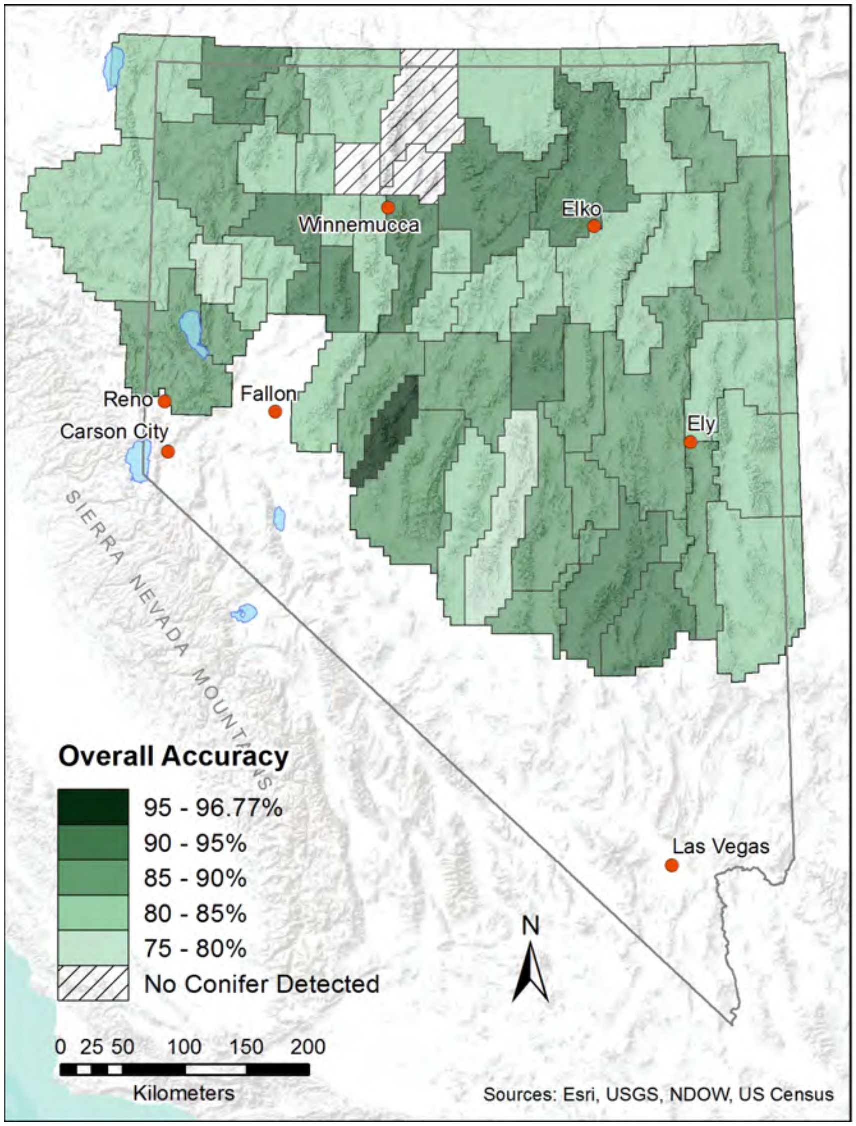


Figure 4. Maps showing conifer extent (left) and percent canopy cover (right) of mapped conifers using automated feature extraction methods within greater sage-grouse habitat in Nevada and California.



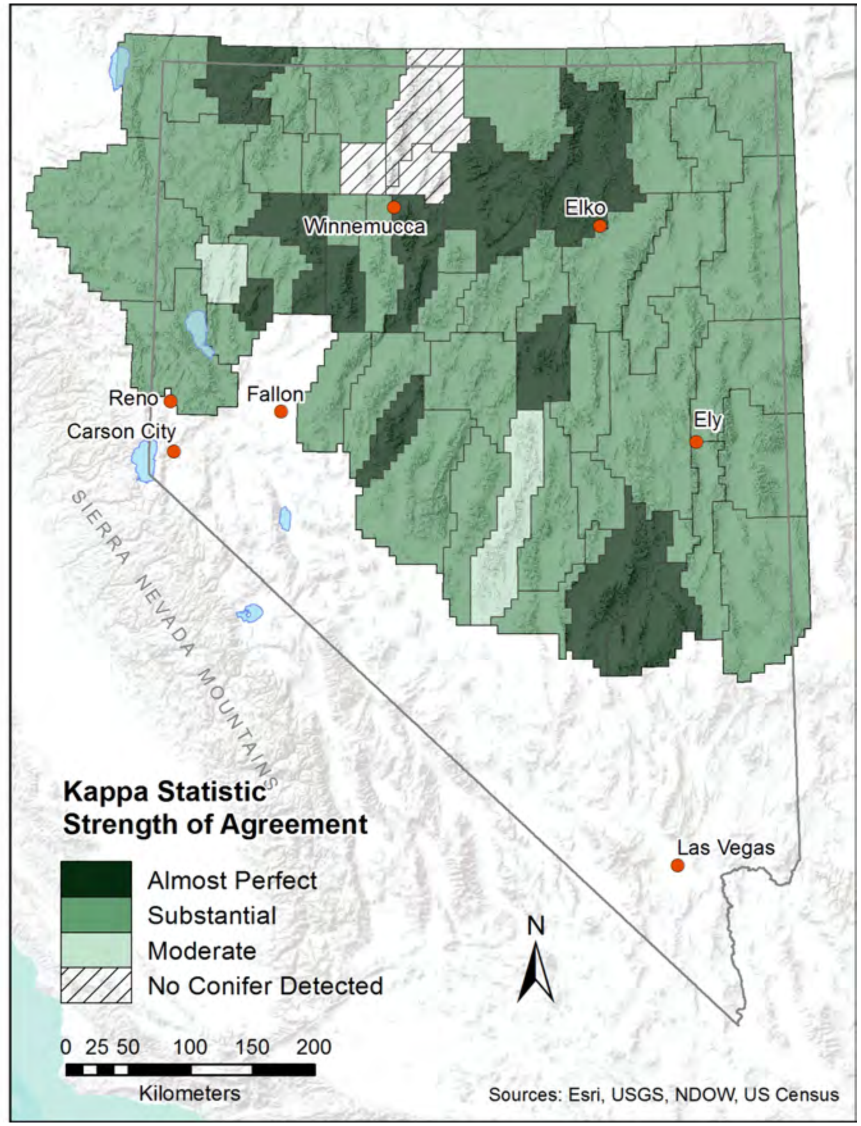


Figure 5. Maps showing overall accuracy (left) and Kappa statistic (right) results by population management unit of mapped conifers at the 1-meter resolution using automated feature extraction methods within greater sage-grouse habitat in Nevada and California.

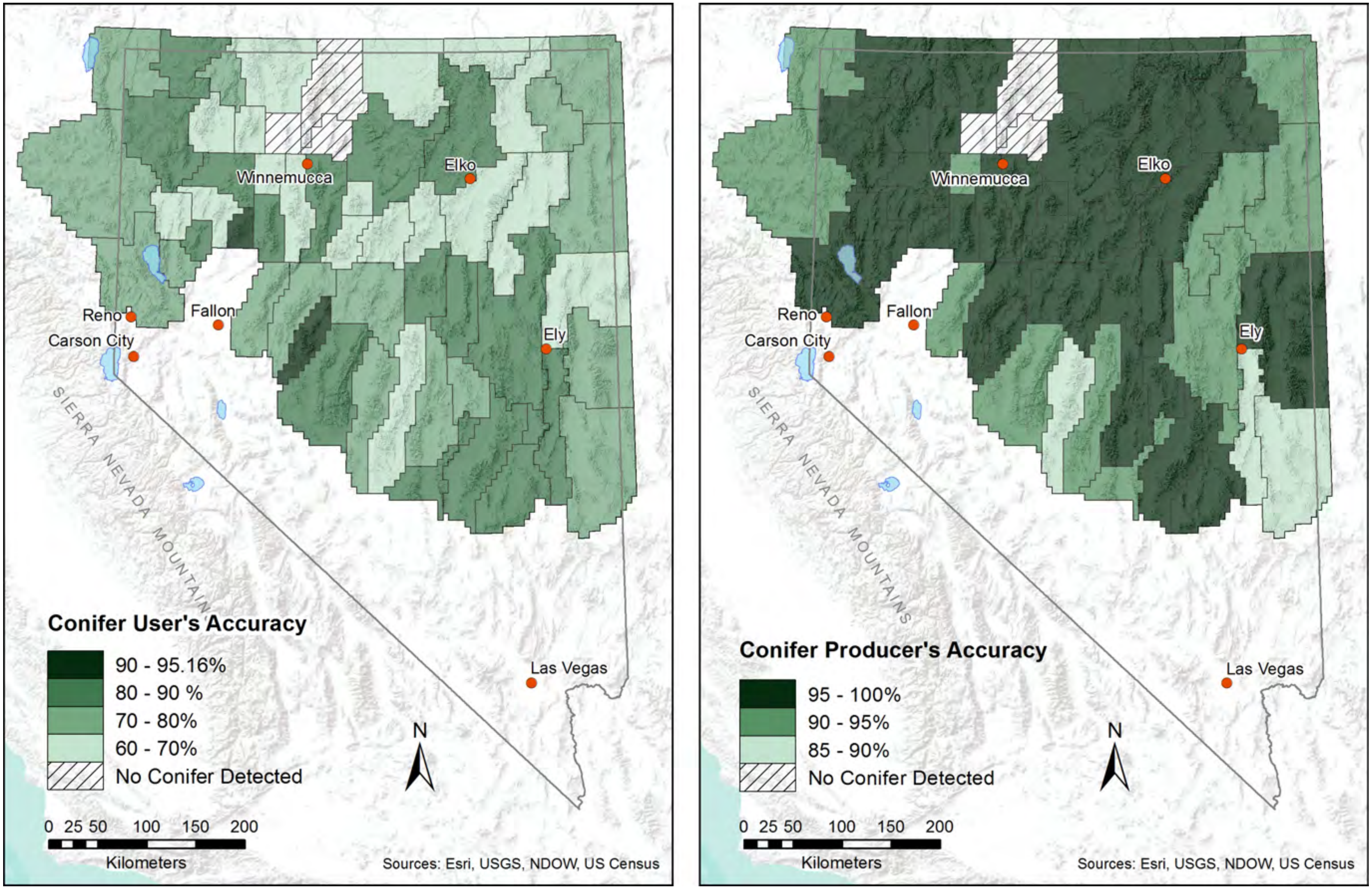


Figure 6. Maps showing user's accuracy (error of commission; left) and producer's accuracy (error of omission; right) by population management unit of mapped conifers at the 1-meter resolution using automated feature extraction methods within greater sage-grouse habitat in Nevada and California.

Discussion

We provide highly accurate maps of conifer distribution at the 1 × 1 m resolution and of continuous canopy cover at the 30 × 30 m resolution across the full extent of mapped sage-grouse habitat in Nevada and northeastern California. Through the process, we produced a framework for implementing Feature Analyst™'s AFE, a highly precise OBIA classification method that heretofore has had limited application at large spatial extents largely because of computational and time demands (Hay and Castilla, 2006; Bruce, 2008; Tsai and others, 2011), but which has proven to be more accurate than traditional supervised classification methods normally conducted at such extents (for example, O'Brien, 2003; Bruce, 2008; Opitz and Blundell, 2008; Blaschke, 2010; Tsai and others, 2011). To the best of our knowledge, we present the only true OBIA-based products across a significant part of the geographic distribution of sagebrush and sage-grouse, which will help facilitate conservation and restoration efforts across large spatial extents. Representation of conifer features in our outputs better reflect ground conditions than 30 × 30 m resolution Landsat-derived conifer products (fig. 7), largely because of the high resolution outputs of our reference imagery.

The high resolution conifer maps provided here can offer a decision support tool for land managers and also help to inform further ecological studies. For example, such maps can help refine models that predict distribution and abundance for a variety of wildlife species that respond to pinyon-juniper in the environment, including sage-grouse populations within Nevada and California (Coates and others, 2015, 2016). Additionally, high resolution conifer maps are necessary to understand the underlying mechanisms (Coates and others, 2017; Prochazka and others, 2017) of how conifers adversely influence sage-grouse population dynamics (Baruch-Mordo and others, 2013). Our percent canopy cover output (smoothed and unsmoothed) have built-in flexibility that allow users to select the cutoffs that are appropriate for their purposes

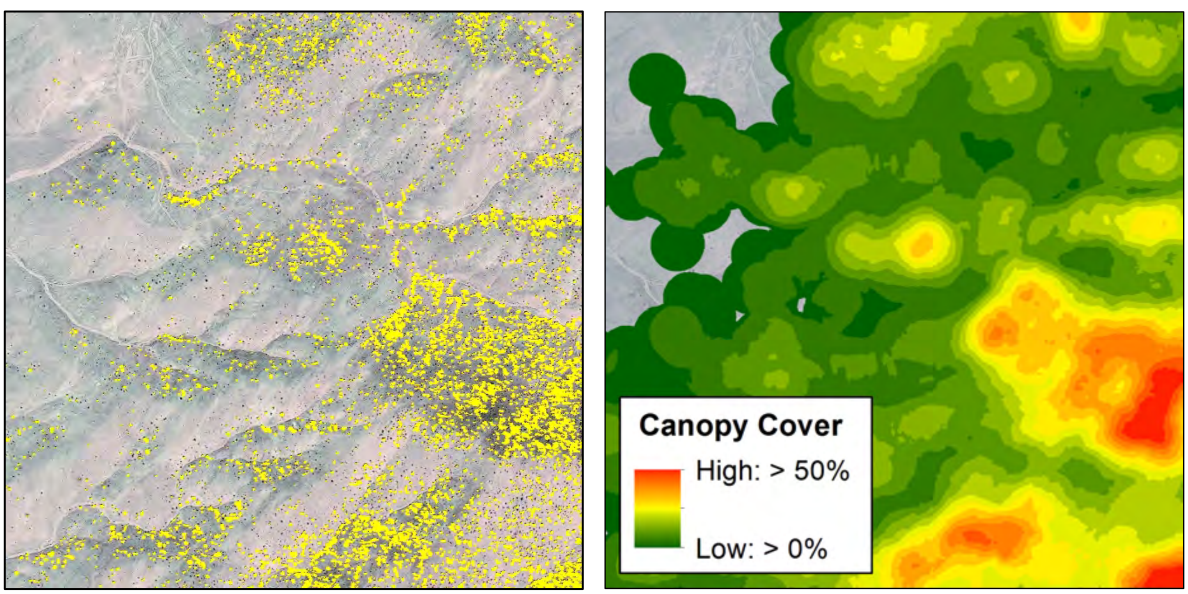


Figure 7. Example conifer classification output overlay (in yellow; left) and percent canopy cover calculation overlay (right) from conifers mapped in the same area of Nevada using automated feature extraction.

(Miller and others, 2000, 2005; Tausch and others, 2009; Falkowski and Evans, 2012). For example, demarcation of a specific cover class can be based on quantified effects of pinyon-juniper on sage-grouse population dynamics (Baruch-Mordo and others, 2013; Coates and others, 2017).

Land managers can further economically value their sites by developing scenarios and assessing how well they meet the specific goals of each project, which can then help streamline allocation of time and resources currently necessary for project appraisals (Opitz and Blundell, 2008; Boswell and others, 2017). At large spatial extents, these high-resolution products can help land managers evaluate and compare candidate sites for conifer removal remotely across large spatial extents (Falkowski and Evans, 2012; Falkowski and others, 2017). In specific regard to sage-grouse, high resolution conifer maps could be used to calculate ecological benefits of removing pinyon-juniper trees to sage-grouse populations by simulating pinyon-juniper removal and integrating results into sage-grouse habitat and demographic models, allowing for quantification of direct improvement to habitat suitability and demographic rates. This process can be valuable for calculating conservation credits as ecological currency for large extent programs such as the State of Nevada Conservation Credit System (2017). Additional use of the cover class settings can refine target removal areas to those within transitional phase 1, identifying areas where trees have the greatest adverse effects on sage-grouse survival (Coates and others, 2017) and, thus, allocate funds to those sites that maximize benefits to sage-grouse (Miller and others, 2008; Baruch-Mordo and others, 2013). These mapping products also enable other non-wildlife related landscape-level management through traditional site-level treatments and facilitates managers to prioritize and efficiently implement restoration projects, which include forage for cattle (Bedell and others, 1997; Soulé and Knapp, 1999; Twidwell and others, 2013), changes in soil erosion patterns (Davenport and others, 1998; Pierson and others, 2010), or reductions of wildfire fuel loads, extent, and severity (Hulet and others, 2014).

The framework we presented (fig. 3) enables the use of intensive AFE to classify target features across an entire region from VHSR imagery, resulting in comprehensive and highly accurate outputs. OBIA methods like AFE that require higher levels of automation are known to be time consuming (Strand and others, 2006; Tsai and others, 2011; Falkowski and Evans, 2012), which has restricted the scope of their application (Falkowski and Evans, 2012). Our framework reduces processing time and computational demand in order to make the implementation of such OBIA methods feasible across relatively large spatial extents. This reduction was primarily accomplished by leveraging Feature Analyst™'s user-friendly, semi-automated, inductive learning algorithms to decrease user investment and processing time (Opitz and Blundell, 2008). We also took advantage of parameters such as the bullseye pattern to reduce the amount of data processed by Feature Analyst™'s models (Opitz and Blundell, 2008). However, AFE and other semi-automated OBIA methods require substantial operator investment (Strand and others, 2006; Tsai and others, 2011; Falkowski and Evans, 2012). For example, to produce our conifer classification, each tile required individualized training polygon development and supervised (often hierarchical) learning runs. The volume of work necessary to map the state required 10 analysts working congruently for several months.

Although the high operator-involvement of Feature Analyst™ promotes the extraction of features that are more accurate to human perception (Opitz and Blundell, 2008), the subjectivity of the inputs decreases reproducibility and increases analysis time (Strand and others, 2006). To reduce this unavoidable cost, we integrated our Feature Analyst™ workflow with many time-saving geoprocessing steps such as analyzing imagery on a tile-by-tile basis, conducting percent canopy cover classification by sectors, and performing validation within PMUs. Geoprocessing steps such as rasterization and mosaicking were iterated within PMUs in ArcGIS using Model Builder (Esri, 2013, Release 10.2, Redlands, California) so that multiple classified tiles could undergo post-processing in quick succession and simultaneously. We also used Model Builder to iterate the calculation and reclassification of percent canopy cover smoothed by the 50-m radius neighborhood within sectors. Post-processing could be further automated by additional iteration across PMUs and sectors, respectively. User-investment could be reduced on the front end by mosaicking the NAIP tiles into a single layer. However, analysis of VHSR imagery at such a large spatial extent remains limited by processing power. Also, Feature Analyst™ has several features that facilitate further automation via batch processing, such as the ability to save training polygons and learning algorithms for repeated use, allowing analysts to use a single training set and model for all imagery and greatly reduce the user-investment and processing time required for each tile (Opitz and Blundell, 2008). We could not use these functions largely because of inconsistent quality of NAIP tiles across our mapping extent. However, such features are available for future applications and could easily be incorporated into this existing framework. Lastly, as improved reference imagery becomes available, outputs are planned to be integrated into spatially explicit maps of contemporary seasonal sage-grouse habitat suitability. Thus, this overarching framework supports the development of "living layers" that reflect existing sage-grouse habitat conditions and provide highly accurate, timely information to land managers operating within and responding to changing landscapes.

Caveats and Comparisons

The accuracy of our conifer classification inspires confidence in its utility for pinyon-juniper removal efforts. However, because our accuracy assessment was not all-encompassing, uncaptured error or variability within PMUs that affects site-level decisions may exist. Accuracies for the PMUs are relatively high (Landis and Koch, 1977), but we calculated wide variability among scores (K_{hat} = 79.1–96.7 percent, fig. 5b) driven by fluctuation in user's accuracies for conifer classification (SD = 8.43; table 3) across the PMUs. Conifer class commission errors (and subsequent omission errors in the non-conifer class) are likely a result of the algorithms' incorrect assignment of shadows and non-target vegetation to the conifer class, which was prevalent in dense canopy cover and riparian areas, respectively. Inclusion of shadows was most likely exaggerated in regions of topographic shading, causing potential overestimation of canopy cover. We attempted to minimize commission by digitizing misclassified features as part of the hierarchical learning process in order to train the learning algorithms to distinguish spectral signatures of conifers from background. However, NAIP DOQQ tiles with low-quality imagery resulted in spectral overlap between conifer and classes with similar signatures. The variation in user's accuracies among PMU mosaics was caused by inconsistent lighting, spectral values, parallax, and processing artifacts among tiles. We addressed these inconsistencies by performing object training on a tile-by-tile basis in order to achieve the highest accuracy for each processed area possible. Unfortunately, seamlines caused by inconsistent image quality were exaggerated as an artifact of this process. Tiles were reclassified if necessary to reduce the seamlines and produce a more realistic, continuous surface.

Even with the relatively high accuracy of OBIA derived layers (Blaschke, 2010), improved accuracy of OBIA methods is particularly necessary for applications at small spatial extents. Higher quality reference imagery will resolve immediate issues such as spectral overlap between target and background features and incongruence among tiles. With the continuous improvement in resolution and the increasing availability of multi- and hyper-spectral imagery due to advancing sensor technology, we expect vast improvement in the ability to effectively extract conifers by spectral signature, and thereby improve image segmentation and AFE methods. Fusions of VHSR imagery with ancillary data sources such as lidar or canopy height models could also enhance the conifer classification process, which could help eliminate commission of shadows or low-growth vegetation by stratifying image cells by height. Lidar and lidar fusions have been used to discern individual trees in merged canopies from peaks in canopy structure (Hirschmugl and others, 2007; Sankey and Glenn, 2011; Jakubowski and others, 2013), which would benefit site-level management planning by estimating the number of trees to be removed. However, implementation of these methods across large spatial extents presents a challenge largely because of limitations on data availability, acquisition costs, and computational power (Tsai and others, 2011).

We chose to use AFE as our method of OBIA because of its reported accuracy (O’Brien, 2005; Bruce, 2008; Opitz and Blundell, 2008; Tsai and others, 2011), yet Spatial Wavelet Analysis (SWA) has been successfully employed for a number of conifer classification products (Falkowski and others, 2006; Strand and others, 2006, 2007, 2008; Falkowski and Evans, 2012). Most recently, Falkowski and others (2017) used SWA to produce high-resolution (1 × 1 m) canopy cover classification of conifers across an 11-State region that included the Great Basin. SWA extracts conifers from imagery by convolving various sized two-dimensional Mexican Hat Wavelet functions, which have a circular shape that emulates tree crowns, to capture variability in tree crown dimension. The output is a circular feature at the location of the detected tree with a diameter specified by the size of the best-fitting wavelet. Although this method has benefits related to less processing time, there are many known disadvantages of using SWA to classify canopy cover. Because SWA classifies image-objects by signal size and shape, it can confuse background features such as roads or streambeds for target features, and it cannot readily differentiate among vegetation types, so it is biased towards errors of commission that require manual correction (Strand and others, 2006; Falkowski and Evans, 2012; Falkowski and others 2017). AFE may not share this bias because it uses similarities in the focal pixel cell and training image-object spectral signatures to segment target features, rather than signal and wavelet pattern. Also, SWA is prone to under-classifying dense canopy areas (Strand and others, 2006; Poznanovic and others, 2014; Falkowski and others, 2017) because the wavelet loses the ability to recognize trees as a target feature when the shape of the signal is no longer circular (Strand and others, 2008). Therefore this method has been reported to be inappropriate in closed canopy systems where canopy cover exceeds 40 percent (Poznanovic and others, 2014; Falkowski and others, 2017). SWA has also been shown to omit trees in shaded regions, particularly in areas with topographic shadows (Falkowski and others, 2017), which represents a challenge given the terrain of Nevada. AFE in Feature Analyst™ does not have a high rate of omission errors in the higher conifer canopy classes (3 percent) because the algorithm can be parameterized to segment image-objects by target spectral properties rather than shape. However, AFE will return dense canopies as a single object.

One of the greatest advantages of using SWA is its multiscale functionality (Strand and others, 2006; Falkowski and others, 2017), but users can achieve the same end with AFE (albeit time-intensive) by using several scales to parameterize the search neighborhood. However, we used known characteristics of conifer size to determine the correct scale of the analysis. We selected the threshold scale of 5 × 5 m because it covered our assumed 3 m^2 cutoff for minimum conifer size, and it returned the highest accuracy output in our initial tests. Also, the 5 × 5 m restriction allowed us to exclude many non-target species that are spectrally inseparable from conifers (fig. 8). This criterion inherently omitted some small conifers, but these trees are estimated to represent a very small percentage of woody biomass (Strand and others, 2008; Poznanovic and others, 2014), and we opted to reduce errors of commission to provide a more conservative and overall accurate classification. In contrast, SWA may misclassify other species as conifers because they meet requisite size and shape criteria. Therefore SWA may overestimate conifer cover in low to no cover areas such as riparian zones and salt flats dominated by other woody plant species. Accurate classification of conifers in low canopy cover areas is critical because sage-grouse are sensitive to small percentage increases in canopy cover, and overestimation can mask regions that represent ecological traps for sage-grouse and could be targeted for pinyon-juniper removal (Baruch-Mordo and others, 2013; Coates and others, 2017).

Nevertheless, AFE and SWA methods have been used to produce canopy cover products specifically to assist managers with sagebrush ecosystem and habitat restoration within the same region, and both methods have inherent advantages and disadvantages. Research that focuses more directly on comparing the two methods at large spatial extents would be highly beneficial, especially regarding: (1) assessment of differences in accuracy among canopy densities to define potential spatial discrepancies in performance; and (2) contrasting sources of commission errors to understand viability and future utility of these methods at different spatial extents. These comparisons may reveal that in some instances, SWA and AFE complement each other, whereas in other instances, one method out-performs the other.

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Appendix A. Error Matrices Results of Mapping Conifers at the 1-Meter Resolution across All Population Management Units Using Intensive Accelerated Feature Extraction Methods within Greater Sage-Grouse Habitat of Nevada and California

[K_{hat}, estimated accuracy coefficient]

Battle Mountain

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	17	8	25	68.00%	
Non-conifer random	0	25	25	100.00%	
Total	17	33	50		
Producer's accuracy	100.00%	75.76%		84.00%	Overall accuracy
				68.00%	K_{hat}

Black Rock

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	17	8	25	68.00%	
Non-conifer random	0	25	25	100.00%	
Total	17	33	50		
Producer's accuracy	100.00%	75.76%		84.00%	Overall accuracy
				68.00%	K_{hat}

Buffalo-Skedaddle

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	281	116	397	70.78%	
Non-conifer random	31	366	397	92.19%	
Total	312	482	794		
Producer's accuracy	90.06%	75.93%		81.49%	Overall accuracy
				62.97%	K_{hat}

Butte/Buck/White Pine

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	294	62	356	82.58%	
Non-conifer random	30	326	356	91.57%	
Total	324	388	712		
Producer's accuracy	90.74%	84.02%		87.08%	Overall accuracy
				74.16%	K_{hat}

Clan Alpine

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	91	25	116	78.45%	
Non-conifer random	1	115	116	99.14%	
Total	92	140	232		
Producer's accuracy	98.91%	82.14%		88.79%	Overall accuracy
				77.59%	K_{hat}

Cortez

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	42	18	60	70.00%	
Non-conifer random	1	59	60	98.33%	
Total	43	77	120		
Producer's accuracy	97.67%	76.62%		84.17%	Overall accuracy
				68.33%	K_{hat}

Desatoya

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	59	3	62	95.16%	
Non-conifer random	1	61	62	98.39%	
Total	60	64	124		
Producer's accuracy	98.33%	95.31%		96.77%	Overall accuracy
				93.55%	K_{hat}

Desert

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	17	8	25	68.00%	
Non-conifer random	0	25	25	100.00%	
Total	17	33	50		
Producer's accuracy	100.00%	75.76%		84.00%	Overall accuracy
				68.00%	K_{hat}

Diamond

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	78	19	97	80.41%	
Non-conifer random	4	93	97	95.88%	
Total	82	112	194		
Producer's accuracy	95.12%	83.04%		88.14%	Overall accuracy
				76.29%	K_{hat}

East Range

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	44	25	69	63.77%	
Non-conifer random	2	67	69	97.10%	
Total	46	92	138		
Producer's accuracy	95.65%	72.83%		80.43%	Overall accuracy
				60.87%	K_{hat}

East Valley

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	171	45	216	79.17%	
Non-conifer random	14	202	216	93.52%	
Total	185	247	432		
Producer's accuracy	92.43%	81.78%		86.34%	Overall accuracy
				72.69%	K_{hat}

Eugenes

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	17	8	25	68.00%	
Non-conifer random	1	24	25	96.00%	
Total	18	32	50		
Producer's accuracy	94.44%	75.00%		82.00%	Overall accuracy
				64.00%	K_{hat}

Fish Creek

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	23	12	35	65.71%	
Non-conifer random	0	35	35	100.00%	
Total	23	47	70		
Producer's accuracy	100.00%	74.47%		82.86%	Overall accuracy
				65.71%	K_{hat}

Gollaher

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	138	49	187	73.80%	
Non-conifer random	10	177	187	94.65%	
Total	148	226	374		
Producer's accuracy	93.24%	78.32%		84.22%	Overall accuracy
				68.45%	K_{hat}

Humboldt

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	35	4	39	89.74%	
Non-conifer random	0	39	39	100.00%	
Total	35	43	78		
Producer's accuracy	100.00%	90.70%		94.87%	Overall accuracy
				89.74%	K_{hat}

Islands

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	55	24	79	69.62%	
Non-conifer random	0	79	79	100.00%	
Total	55	103	158		
Producer's accuracy	100.00%	76.70%		84.81%	Overall accuracy
				69.62%	K_{hat}

Jackson

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	21	9	30	70.00%	
Non-conifer random	1	29	30	96.67%	
Total	22	38	60		
Producer's accuracy	95.45%	76.32%		83.33%	Overall accuracy
				66.67%	K_{hat}

Kawich

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	47	11	58	81.03%	
Non-conifer random	4	54	58	93.10%	
Total	51	65	116		
Producer's accuracy	92.16%	83.08%		87.07%	Overall accuracy
				74.14%	K_{hat}

Limbo

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	21	14	35	60.00%	
Non-conifer random	0	35	35	100.00%	
Total	21	49	70		
Producer's accuracy	100.00%	71.43%		80.00%	Overall accuracy
				60.00%	K_{hat}

Lincoln

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	239	67	306	78.10%	
Non-conifer random	32	274	306	89.54%	
Total	271	341	612		
Producer's accuracy	88.19%	80.35%		83.82%	Overall accuracy
				67.65%	K_{hat}

Lone Willow

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	16	9	25	64.00%	
Non-conifer random	0	25	25	100.00%	
Total	16	34	50		
Producer's accuracy	100.00%	73.53%		82.00%	Overall accuracy
				64.00%	K_{hat}

Majuba 1-2

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	33	6	39	84.62%	
Non-conifer random	0	39	39	100.00%	
Total	33	45	78		
Producer's accuracy	100.00%	86.67%		92.31%	Overall accuracy
				84.62%	K_{hat}

Majuba 3-4

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	25	11	36	69.44%	
Non-conifer random	0	36	36	100.00%	
Total	25	47	72		
Producer's accuracy	100.00%	76.60%		84.72%	Overall accuracy
				69.44%	K_{hat}

Massacre

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	79	19	98	80.61%	
Non-conifer random	1	97	98	98.98%	
Total	80	116	196		
Producer's accuracy	98.75%	83.62%		89.80%	Overall accuracy
				79.59%	K_{hat}

Nightengale

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	19	6	25	76.00%	
Non-conifer random	0	25	25	100.00%	
Total	19	31	50		
Producer's accuracy	100.00%	80.65%		88.00%	Overall accuracy
				76.00%	K_{hat}

North Fork

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	61	13	74	82.43%	
Non-conifer random	0	74	74	100.00%	
Total	61	87	148		
Producer's accuracy	100.00%	85.06%		91.22%	Overall accuracy
				82.43%	K_{hat}

O'Neil

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	23	13	36	63.89%	
Non-conifer random	0	36	36	100.00%	
Total	23	49	72		
Producer's accuracy	100.00%	73.47%		81.94%	Overall accuracy
				63.89%	K_{hat}

Pine Forest

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	20	5	25	80.00%	
Non-conifer random	0	25	25	100.00%	
Total	20	30	50		
Producer's accuracy	100.00%	83.33%		90.00%	Overall accuracy
				80.00%	K_{hat}

Reese River

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	178	39	217	82.03%	
Non-conifer random	13	204	217	94.01%	
Total	191	243	434		
Producer's accuracy	93.19%	83.95%		88.02%	Overall accuracy
				76.04%	K_{hat}

Ruby Valley

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	120	60	180	66.67%	
Non-conifer random	7	173	180	96.11%	
Total	127	233	360		
Producer's accuracy	94.49%	74.25%		81.39%	Overall accuracy
				62.78%	K_{hat}

Sahwave 1-2

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	22	3	25	88.00%	
Non-conifer random	1	24	25	96.00%	
Total	23	27	50		
Producer's accuracy	95.65%	88.89%		92.00%	Overall accuracy
				84.00%	K_{hat}

Schell-Antelope

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	149	64	213	69.95%	
Non-conifer random	5	208	213	97.65%	
Total	154	272	426		
Producer's accuracy	96.75%	76.47%		83.80%	Overall accuracy
				67.61%	K_{hat}

Sheldon

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	49	9	58	84.48%	
Non-conifer random	0	58	58	100.00%	
Total	49	67	116		
Producer's accuracy	100.00%	86.57%		92.24%	Overall accuracy
				84.48%	K_{hat}

Shoshone

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	40	20	60	66.67%	
Non-conifer random	1	59	60	98.33%	
Total	41	79	120		
Producer's accuracy	97.56%	74.68%		82.50%	Overall accuracy
				65.00%	K_{hat}

Snake

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	53	17	70	75.71%	
Non-conifer random	2	68	70	97.14%	
Total	55	85	140		
Producer's accuracy	96.36%	80.00%		86.43%	Overall accuracy
				72.86%	K_{hat}

Sonoma

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	46	9	55	83.64%	
Non-conifer random	0	55	55	100.00%	
Total	46	64	110		
Producer's accuracy	100.00%	85.94%		91.82%	Overall accuracy
				83.64%	K_{hat}

South Fork

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	114	55	169	67.46%	
Non-conifer random	3	166	169	98.22%	
Total	117	221	338		
Producer's accuracy	97.44%	75.11%		82.84%	Overall accuracy
				65.68%	K_{hat}

Spring-Snake Valley

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	140	52	192	72.92%	
Non-conifer random	7	185	192	96.35%	
Total	147	237	384		
Producer's accuracy	95.24%	78.06%		84.64%	Overall accuracy
				69.27%	K_{hat}

Steptoe-Cave

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	93	18	111	83.78%	
Non-conifer random	11	100	111	90.09%	
Total	104	118	222		
Producer's accuracy	89.42%	84.75%		86.94%	Overall accuracy
				73.87%	K_{hat}

Stillwater

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	37	12	49	75.51%	
Non-conifer random	4	45	49	91.84%	
Total	41	57	98		
Producer's accuracy	90.24%	78.95%		83.67%	Overall accuracy
				67.35%	K_{hat}

Three Bar

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	84	13	97	86.60%	
Non-conifer random	4	93	97	95.88%	
Total	88	106	194		
Producer's accuracy	95.45%	87.74%		91.24%	Overall accuracy
				82.47%	K_{hat}

Toiyabe

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	109	41	150	72.67%	
Non-conifer random	2	148	150	98.67%	
Total	111	189	300		
Producer's accuracy	98.20%	78.31%		85.67%	Overall accuracy
				71.33%	K_{hat}

Trinity 1-2

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	23	2	25	92.00%	
Non-conifer random	1	24	25	96.00%	
Total	24	26	50		
Producer's accuracy	95.83%	92.31%		94.00%	Overall accuracy
				88.00%	K_{hat}

Tuscarora

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	21	4	25	84.00%	
Non-conifer random	0	25	25	100.00%	
Total	21	29	50		
Producer's accuracy	100.00%	86.21%		92.00%	Overall accuracy
				84.00%	K_{hat}

Virginia-Pahrah

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	139	39	178	78.09%	
Non-conifer random	4	174	178	97.75%	
Total	143	213	356		
Producer's accuracy	97.20%	81.69%		87.92%	Overall accuracy
				75.84%	K_{hat}

Vya

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	128	49	177	72.32%	
Non-conifer random	12	165	177	93.22%	
Total	140	214	354		
Producer's accuracy	91.43%	77.10%		82.77%	Overall accuracy
				65.54%	K_{hat}

Zone 1 (Monitor)

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	80	26	106	75.47%	
Non-conifer random	10	96	106	90.57%	
Total	90	122	212		
Producer's accuracy	88.89%	78.69%		83.02%	Overall accuracy
				66.04%	K_{hat}

Zone 2 (Monitor)

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	101	62	163	61.96%	
Non-conifer random	6	157	163	96.32%	
Total	107	219	326		
Producer's accuracy	94.39%	71.69%		79.14%	Overall accuracy
				58.28%	K_{hat}

Zone 3 (Monitor)

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	110	39	149	73.83%	
Non-conifer random	3	146	149	97.99%	
Total	113	185	298		
Producer's accuracy	97.35%	78.92%		85.91%	Overall accuracy
				71.81%	K_{hat}

Zone 4 (Monitor/Quinn)

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	40	13	53	75.47%	
Non-conifer random	0	53	53	100.00%	
Total	40	66	106		
Producer's accuracy	100.00%	80.30%		87.74%	Overall accuracy
				75.47%	K_{hat}

Zone 5 (Quinn)

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	130	23	153	84.97%	
Non-conifer random	1	152	153	99.35%	
Total	131	175	306		
Producer's accuracy	99.24%	86.86%		92.16%	Overall accuracy
				84.31%	K_{hat}

Zone 6 (Quinn)

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	124	17	141	87.94%	
Non-conifer random	3	138	141	97.87%	
Total	127	155	282		
Producer's accuracy	97.64%	89.03%		92.91%	Overall accuracy
				85.82%	K_{hat}

Zone 7 (Quinn)

	Conifer	Non-conifer	Total	User's accuracy	
Conifer random	22	3	25	88.00%	
Non-conifer random	2	23	25	92.00%	
Total	24	26	50		
Producer's accuracy	91.67%	88.46%		90.00%	Overall accuracy
				80.00%	K_{hat}

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