Chapter 6: Mapping Forest Conditions: Past, Present, and Future

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Introduction

Mapping and mapped data have always been critical to public land managers and researchers for identifying and characterizing wildlife habitat across scales, monitoring species and habitat change, and predicting and planning future scenarios. Maps and mapping protocols are often incorporated into wildlife and habitat management plans, as is the case with the California spotted owl (*Strix occidentalis occidentalis*), a subspecies of management concern. Current spotted owl managers on all Sierra Nevada national forests use canopy cover and tree size guidelines designed to provide habitat for sensitive species (Chopping et al. 2012, Moghaddas et al. 2010) and to estimate accurately these important habitat metrics across scales from nest trees and the area surrounding them to broader scale characterization of core foraging and home ranges. These mapping tasks can be challenging in California forests, particularly in the Sierra Nevada because they exhibit great variability in composition, cover, and topography, and complex legacies of fire and logging (Hyde et al. 2005).

In this chapter, I have focused on mapping technology that can be used in the analysis of owl use of forested habitat. I reviewed and summarized 18 peer-reviewed papers published from 1992 through 2013 that described the use of remote sensing, aerial imagery, or other mapped products to assess forest structure used by California spotted owls across scales and that also were specific about mapping protocols. Because many of the newer papers used new remote sensing technologies such as light detection and ranging (LiDAR), I have presented a retrospective of mapping methods before the detailed summary of the literature on California spotted owl.

Owl Habitat Mapping Methods, Strengths, and Weaknesses

Historical Mapping Technology

Approaches to mapping wildlife habitat have been varied. They have included a range of remote sensing products and methods, manual delimitation and automated classifications, and mapping at many scales (Gottschalk et al. 2005, McDermid et al.

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2005). Data describing owl habitat have been gathered from field surveys (e.g., Bond et al. 2004), black and white or color air photos (e.g., Dugger et al. 2011, Ripple et al. 1997), or digital aerial imagery (e.g., Seamans and Gutiérrez 2007); and existing mapped products such as timber survey maps (e.g., Blakesley et al. 1992, Call et al. 1992), Landsat-derived vegetation maps (e.g., Bond et al. 2009, Hines et al. 2005), and fire-severity maps (e.g., Roberts et al. 2011). Remotely sensed imagery at fine spatial resolution (e.g., 1 m [3.3 ft]) and moderate resolution (e.g., 30 m [99 ft]) has also been used. Table 6-1 summarizes the types of remote sensing and mapping products commonly used for the mapping of spotted owl habitat.

Aerial Photography

Aerial photographs provide spatially detailed records of landscapes (Morgan et al. 2010). Despite the increase in the number and types of digital sensors available to managers and scientists, aerial photography remains a valuable tool for habitat

Table 6-1—Map products typically used to understand California spotted owl habitat

Type	Product	Data scale/resolution	Example reference
Aerial photography	Black and white imagery	1:12,000 to 1:40,000	Ripple et al. 1997
Aerial photography	Color photography	1:12,000 to 1:40,000	Blakesley et al. 2005, Dugger et al. 2011
Aerial photography	Color infrared photography	1:12,000 to 1:20,000; 1 m	Lee et al. 2013
Aerial photography	Digital orthophoto quadrangles	1:20,000 to 1:24,000; 1 m	Seamans and Gutiérrez 2007
Optical remote sensing	NAIP	1 m	Lee et al. 2013, Williams et al. 2011
Optical remote sensing	IKONOS (Satellite)	1 to 4 m	Moghaddas et al. 2010
Optical remote sensing	QuickBird	0.6 to 2.5 m	Chopping et al. 2012
Optical remote sensing	Landsat-5 Thematic Mapper	30 m	Hunter et al. 1995, Moen and Gutiérrez 1997
Optical remote sensing	Relative differenced normalized burn ratio	30 m	Roberts et al. 2011
Optical remote sensing	USFS EVEG	30 m	Bond et al. 2009, Hines et al. 2005
LiDAR	Airborne discrete return	10- to 50-cm footprint	García-Feced et al. 2011, Hyde et al. 2005
LiDAR	Airborne waveform	25- to 50-m footprint	Chopping et al. 2013
Existing mapped products	Timber strata maps	1:20,000; misc.	Blakesley et al. 1992, Irwin et al. 2007
Existing mapped products	FRAP fire perimeter maps		Bond et al. 2002

NAIP = National Agriculture Imagery, LiDAR = light detection and ranging, USFS EVEG = U.S. Forest Service existing vegetation, FRAP = Fire Resources and Assessment Program.

mapping for several reasons. First, aerial photographs predate satellite imagery; in California, imagery archives include images from the 1930s onward (Morgan et al. 2010). Second, the spatial detail provided by aerial photography is high, even when analog photographs are digitized. For example, a 1:20,000-scale photograph scanned at 200 dots per inch (dpi) will provide a digital image of 2.54-m (8.38-ft) resolution, and at 600 dpi yields 0.85-m (2.8-ft) resolution (Jensen 2000). This compares favorably to Landsat pixels, which are 30-m resolution and are similar to current high-resolution sensors such the QuickBird sensor. Third, when digitized, aerial photographs can be analyzed with powerful image analysis techniques. Although many of these techniques were originally developed for satellite imagery, they have also expanded upon the range of analysis techniques now available for aerial photographs (Cohen et al. 1996, Morgan et al. 2010).

The spatial scale of aerial photography influences how it is used. Large-scale (1:2,400 to 1:1,200) photographs can be used to map individual trees, stream reaches, and fine-scale habitat photographs at 1:20,000-to 1:4,800-scale are used to map forest stand polygons, vegetation communities, and habitat patches. Photographs of 1:40,000-scale-and-smaller are useful for general land cover with minimum mapping units (MMUs) of 2 to 4 ha (5 to 10 ac) (Wulder 1998). Aerial photographs are captured most commonly as panchromatic (black and white visible), color, or false-color infrared (CIR). These can be analyzed manually, with a trained analyst tracing boundaries between land cover patches (e.g., Chatfield 2005), and in more automated fashion, using similar algorithms pioneered in remote sensing (Cohen et al. 1996).

A standard format for digital aerial photographs is the digital orthophoto quadrangle (DOQ), which uses a standard image rectification procedure that aligns the image with longitude and latitude or other coordinate system. The U.S. Geological Survey (USGS) provides the largest catalog of DOQs, which may exist as far back as the early part of the 20th century. Typical spatial resolutions for DOQs are 1 m and less. More recently (since 2005 in California), the National Agriculture Imagery Program (NAIP) has been providing free periodic (usually every 5 years) digital CIR aerial imagery at 1-m resolution during the agricultural growing seasons in the continental United States. These images have proved useful for forest and habitat mapping (Cleve et al. 2008, Jakubowski et al. 2013a).

Landsat

The launch of the Earth Resources Technology Satellite 1, or ERTS-1 (ERTS-1) (later renamed Landsat-1) in 1972 (Lauer et al. 1997, Melesse et al. 2007) permanently changed the way remote sensing served resource management, although not immediately. From 1980 to 2000, there was nearly 20 years of increasing use of Landsat imagery by land managers and scientists for mapping forest vegetation (Franklin et al. 2000), particularly in California. Landsat-5 was launched in 1984 with the Thematic Mapper (TM) moderate resolution (30-m [99-ft]), six-band multispectral (typically broad spectral information in the visible to near-infrared light) sensor on board, and became the workhorse for remote sensing of land cover (Cohen and Goward 2004, Wulder et al. 2012). Throughout the 1980s and 1990s, the USDA Forest Service (USFS) and the California Department of Forestry and Fire Protection collaborated in California to produce a statewide Land Cover Mapping and Monitoring Program (LCMMP) to improve the quality and capability of monitoring data, and to minimize costs for statewide land cover monitoring (Levien et al. 2002). The mapping project aimed to support resource inventory, fire management, and habitat conservation goals, and an initial goal was to update these maps to quantify land cover changes every 6 years with the collaboration of the California Division of Forestry and Fire Protection (Franklin et al. 2000). Their initial method involved image segmentation into forest polygons (stands) using spectral and textural inputs, and either unsupervised classification or linear spectral mixed analysis. Results were calibrated with Forest Inventory and Analysis (FIA) data. Map attributes include a vegetation life-form class (e.g., conifer, hardwood, chaparral), vegetation type from the Classification and Assessment with Landsat of Visible Ecological Groupings (CALVEG) classification scheme, and canopy cover and size class estimates for forest stands. A Kauth Thomas algorithm (a transformation of spectral data to brightness, greenness, and wetness) applied to multitemporal Landsat imagery provided information for magnitude and direction of land cover change (Rogan et al. 2003).

The mapping protocol has evolved over time and been updated by the USFS when needed, and now forms the basis of EVEG ("existing vegetation"). EVEG is a Landsat-derived product that captures vegetation characteristics using automated, systematic procedures that map large areas of California and is supplemented with onsite field visits. The current map attributes consist of vegetation types using the CALVEG classification system and forest structural characteristics such as tree and shrub canopy cover and tree stem diameters. Current map product characteristics include a 1-ha (2.5-ac) MMU for most vegetation conditions (there is no MMU for lakes and conifer plantations); life form (conifer, mix, hardwood, shrub, grass, barren, agriculture, urban, ice/snow, water), within-life-form classes that are "cross-walked" to state and regional vegetation mapping standards, information on canopy closure of conifer and hardwood forests, mapped as a function of canopy closure in 10 percent classes, and size of overstory tree as interpreted from aerial photography and satellite imagery.

Vegetation maps derived from Landsat data have been used widely to study California spotted owl habitat (Bond et al. 2004, Hunter et al. 1995, Moen and Gutiérrez 1997). Landsat imagery, as well as the statewide vegetation map product derived from Landsat (i.e., EVEG), has been used since the 1990s for mapping wildlife habitat (Gottschalk et al. 2005) and is being used increasingly in sophisticated species distribution models that map habitat suitability for important wildlife species in California. The broad coverage and spectral detail of the Landsat sensors are useful for large-coverage mapping of species and canopy cover, but this imagery is not able to detect the residual tree component of forests dominated by medium-sized trees that is a critical component driving use by owls in these younger forests (García-Feced et al. 2011, Moen and Gutiérrez 1997). Residual trees are large trees within younger forests that may possibly serve as nest trees and influence forest stand temperature. These detailed aspects of forest structure are now better able to be mapped using a range of “active” remote sensing methods, such as LiDAR.

High Spatial Resolution Imagery

There have been a number of launches of satellites carrying high spatial resolution (approximately 5 m [16.5 ft] or less) multispectral sensors that have been used to map forests. The first of these was IKONOS, which was launched in 1999 with a 3- to 5-day return interval and imaged in panchromatic (1-m [3.3-ft]) and multispectral (4-m [13.2-ft]) modes. The QuickBird satellite (panchromatic band = 60 cm [24 in], multispectral bands = 2.5 m [8.3 ft]) was launched in 2001, and 2003 saw the launch of the OrbView satellite, which acquires multispectral imagery in either multispectral (4-m [13.2-ft]) or panchromatic (1-m [3.3-ft]) mode. In 2008, RapidEye was launched with five satellites as part of a public-private partnership with numerous European partners. This satellite constellation provides almost daily coverage of the Earth at 6.5-m (21.5-ft) resolution and was the first commercial satellite program to include the red-edge band, which is sensitive to changes in chlorophyll content, and therefore useful for vegetation mapping. WorldView-2 was launched in 2009 with an eight-band multispectral sensor (including a red-edge band) operating at 0.5 m (1.7 ft) in panchromatic and 1.8 m (5.9 ft) in the multispectral bands. These sensors provide detailed imagery with a timely repeat schedule and have been used to map forest habitat globally, although only IKONOS has been used in the context of California spotted owl mapping (Moghaddas et al. 2010).

Current and Emerging Technology

LiDAR

LiDAR provides highly detailed, extensive, and accurate vegetation structure data, which has long been identified as a key element of organisms' habitats (Lefsky et al. 2002, Popescu and Wynne 2004, Vierling et al. 2008). LiDAR data are collected from a laser-emitter scanner linked to an accurate positioning system. The round-trip time between pulse origination and return from target is measured, allowing the instrument to calculate the distance to a target object. LiDAR data can be broadly categorized into three classes depending on the type of sensor and deployment: (1) ground-based LiDAR, which samples the scattering returned by the entire laser pulse over a wide range of zenith angles and azimuth angles as it passes through the canopy from a stationary ground-based scanner (Henning and Radtke 2006, Strahler et al. 2008, Zhao et al. 2011); (2) small-footprint discrete return data in which the spatial coordinates of typically four discrete returns per laser pulse are recorded (Lefsky et al. 2002); and (3) large-footprint waveform data in which the pulse-return intensity over time is digitized (Lefsky 2010, Merrick et al. 2013, Vierling et al. 2008). Aircraft-based systems use onboard global positioning system (GPS) and inertial measurement units to establish position, whereas ground-based LiDAR uses GPS alone. The resolution and quality of the data depend on both the scanner and the pulse density (Merrick et al. 2013). The resulting data are either a detailed three-dimensional point cloud (e.g., ground and airborne LiDAR) or a collection of intensity returns (waveform); each of these can be manipulated in numerous ways to derive point-based and raster-based LiDAR metrics that capture aspects of the forest structure such as individual trees (Jakubowski et al. 2013b, Li et al. 2012) or other derived metrics. Most of the current literature describing LiDAR and wildlife habitat focuses on aircraft-based discrete return small-footprint LiDAR.

LiDAR metrics—

Numerous LiDAR metrics derived from the LiDAR point cloud have proved to be useful in wildlife habitat studies. Merrick et al. (2013) outlines primary metrics (those that can be derived directly from the LiDAR point cloud) and secondary metrics (those that are modeled based on LiDAR and field data) that have been used in wildlife studies. Primary metrics include canopy metrics (e.g., canopy surface model, canopy cover/closure, canopy/vegetation height model, canopy/vegetation profiles, canopy base height, canopy volume); vertical profile metrics (e.g., coefficient of variation of hits, foliage height diversity, standard deviation of vegetation height, mean absolute deviation height, vertical distribution of hits); topographic products (e.g., Digital Terrain Model, Digital Elevation Model and LiDAR return intensity). Secondary metrics include aboveground biomass, basal area, canopy complexity/diversity, tree diameter at breast height (d.b.h.), leaf area index (l.a.i.), timber/vegetation volume, and vertical distribution ratio. These metrics have been used to predict vegetation structure (e.g., biomass) and to scale-up field measurements to broader scales (Gonzalez et al. 2010; Hyde et al. 2005; Kane et al. 2011, 2015, 2013; Vierling et al. 2008, Wulder et al. 2008) to predict species performance based on structural associations (Lesak et al. 2011), to aid in vegetation classification and mapping (Swatantran et al. 2011), and in species distribution models to predict species presence or diversity.

Very high resolution imagery and microsatellites—
The 21st century can be characterized, in remote sensing terms, by the increased interest by private industry in the Earth observation domain (Melesse et al. 2007). There are several private companies providing high spatial resolution imagery at cost (e.g., IKONOS, QuickBird, Rapideye, and GeoEye). Additionally, there are numerous companies pioneering the deployment of so-called microsatellites, which are small and operate in low Earth orbit (Kramer and Cracknell 2008). Many of these have spatial resolutions of less than 1 m and operate in the multispectral and panchromatic mode. With multiple satellites operating in a constellation, image acquisition rates are expected to increase to more than one per day for some areas of the Earth. Finally, Google Earth™ (http://earth.google.com) has transformed the ways in which scientists and researchers can access and use high spatial resolution imagery, including assessing wildlife habitat (e.g., Hughes et al. 2011).

Characterizing Habitat Across Scales

Eighteen peer-reviewed journal articles from 1992 through 2013 revealed use of mapping technology to investigate California spotted owl habitat across scales (table 6-2). The organization of this review follows the habitat scales discussed in chapter 3 (i.e., nest, nest stand, core area, foraging habitat, and home range), but it was unclear from reading some papers what was the scale of investigation, so I categorized them loosely. There are tradeoffs among desired resolution, scale of imagery, and needed data given the application (e.g., moderate- to course-scale imagery such as Landsat is not appropriate for fine-scale mapping of habitat). Most papers used mapping technology to characterize forest structure around owl sites. The characterization of forest structure often involves the use of a fixed-radius buffer centered on nest sites or primary roost areas. The radius length dictates the

Table 6-2—Literature describing the mapping of California spotted owl habitat across scales

Reference	Map product/type	Nest	Stand	Core area	Foraging habitat	Home range	Study area
Bias and Gutiérrez 1992	Landsat-5 TM (Thematic mapper)			✓			Eldorado and Tahoe NF
Call et al. 1992	Field surveys; timber strata maps			✓	✓		Tahoe NF
Moen and Gutiérrez 1997	Landsat-5 TM			✓	✓	✓	Central Sierra Nevada
Lahaye et al. 2001	Landsat			✓	✓		San Bernardino Mountains
Temple and Gutiérrez 2002	Landsat: USFS EVEG			✓			Eldorado and Tahoe NF
Bond et al. 2002	CalFire Fire perimeter-maps			✓			Arizona, California, New Mexico
Bond et al. 2004	Landsat: USFS EVEG	✓	✓				Eldorado NF
Blakesley et al. 2005	Color aerial photography		✓	✓			Lassen NF
Hines et al. 2005	Landsat: USFS EVEG					✓	Southern California
Hyde et al. 2005	LiDAR: Waveform		✓				Sierra NF
Seamans and Gutiérrez 2007	Digital orthophoto quadrangles				✓	✓	Central Sierra Nevada
Irwin et al. 2007	Timber strata maps				✓		Northern California
Bond et al. 2009	Landsat: USFS EVEG; Relative differenced normalized burn ratio (dRNBR)			✓	✓	✓	Sequoia NF
Phillips et al. 2010	Digital orthophoto quadrangles and color aerial photographs		✓	✓			Eldorado and Tahoe NF
Moghaddas et al. 2010	IKONOS		✓	✓	✓		Plumas-Lassen NF
García-Feced et al. 2011	Discrete return LiDAR	✓	✓				Eldorado NF
Roberts et al. 2011	RdNBR		✓	✓			Yosemite NP
Williams et al. 2011	NAIP					✓	Eldorado and Tahoe NF
Lee et al. 2013	Color and CIR aerial photography; NAIP		✓				San Bernardino Mountains

USFS EVEG = U.S. Forest Service existing vegetation; NAIP = National Agriculture Imagery Program; LiDAR = light detecton and range, national forest; np = national park, CIR = color infrared.

scale of focus; and literature reports examples of radii <100 m (330 ft) (e.g., Call et al. 1992, Hyde et al. 2005) to >1 km (3,300 ft) (e.g., Dugger et al. 2011, Seamans and Gutiérrez 2007) covering circular areas from 1 ha (nest tree and stand scale) to greater than 1000 ha (2,500 ac; home range scale). The circular area described is then characterized using mapped data: either created new from field surveys, black and white or color air photos, or other remotely sensed imagery such as Landsat, or through the use of existing mapped products such as timber survey maps, Landsat-derived vegetation maps, or fire-severity maps. These results are often compared with an area of similar size that does not contain nest trees (e.g., a randomly selected stand). Other methods include the characterization of forests within some other noncircular area (e.g., minimum convex polygons describing nest and roost sites as in Moen and Gutiérrez (1997)] and Irwin et al. (2007). Existing mapped products have also been used to aid in sampling design, as in Bond et al. (2004) who used the USFS EVEG habitat map to identify the four strata in which to locate their random plots.

Mapping Nests and Nest Trees

Spotted owls nest in forests with dense canopy cover and large (>76 cm [30.5 in] d.b.h.) trees. They will use forests with medium-sized trees if they have dense canopy cover and residual trees (Bias and Gutiérrez 1992, Moen and Gutiérrez 1997). The ability to map individual trees and critical structural elements from remote sensing has been enhanced recently through the use of LiDAR (García-Feced et al. 2011, Hyde et al. 2005). Although canopy cover estimates from optical remote sensing are reliable, the mapping of individual and residual trees is difficult with coarse-scale optical imagery such as Landsat, particularly in dense canopy. García-Feced et al. (2011) evaluated the ability of LiDAR data to map these critical habitat elements in the Tahoe National Forest. They surveyed for spotted owls within this area during 2007 through 2009 and located four nest trees. They then used the LiDAR data to estimate the number, density, and pattern of residual trees (90 cm [36 in] d.b.h.) and to estimate canopy cover within 200 m of each of the nest trees (a circular area of 12.6 ha [31.5 ac]). They found that nest trees were surrounded by large numbers of residual trees and high canopy cover, and the LiDAR-based estimates agreed closely with residual tree counts and canopy cover estimates based on field data collected within 100 m (3 ha [7.5 ac]) of these nest trees.

Mapping Nest Stand Characteristics

California spotted owls nest and roost in complex, multlayered, late-successional forests with high canopy closure and cover, and numerous large trees (chapter 3). Using the classical buffer approach, Blakesley et al. (2005) mapped the forest stands surrounding 67 spotted owl sites using color aerial photographs, digital orthophoto quadrangles (from 1993 and 1998), and timber sale information within circular plots (with radii up to 2.4 km) in northeastern California. They examined the relationships between habitat composition in the area surrounding nest trees and variation in nest success over time (1990 through 2000) and site occupancy, apparent survival probability, and reproductive output over time (1993 through 1998). They found that large trees with high canopy cover were important for site occupancy at the stand scale (e.g., 203 ha) within the nest area, and the amount of nonforested areas and forest cover types not used for nesting or foraging negatively influenced occupancy. Additionally, the presence of large remnant trees within the nest stand facilitated nest success. They conducted their analysis at two spatial scales: nest area (203 ha [507 ac]) and core area (814 ha [325 ac]).

The first study to evaluate the use of LiDAR for mapping California spotted owl habitat was Hyde et al. (2005). They used large footprint, waveform LiDAR data acquired for the Sierra National Forest in October 1999 (leaf-on) to map forest structure: canopy height, canopy cover, and aboveground biomass. They used a LiDAR called Laser Vegetation Imaging Sensor, which is a full waveform-digitizing system that records the vertical distribution of target surfaces with 30-cm (12-in) vertical resolution. This was a large footprint system with a 12.5-m (31.5-ft) radius footprint on the ground. They compared LiDAR footprint returns to field data gathered in circular plots with an inner plot of 0.07-ha (1.18-ac; 15-m or 50-ft radius) and an outer plot of 1-ha (2.5-ac; 56.4-m or 186.1-ft radius). Results were encouraging: field and LiDAR canopy structure measures showed good agreement across a range of elevation and slope. They suggested that the correlation between the field plots and LiDAR data was amenable to scaling, and thus LiDAR was useful to characterize montane forest canopy structure over the wide range of environmental conditions that occur over the Sierra National Forest and might be useful to use for habitat mapping over large areas. The location of nest trees in relation to forest edges was examined by Phillips et al. (2010), who used a vegetation map of the Eldorado and Tahoe National Forests that had been created using aerial photography and digital orthophoto quadrangles from 1998 and 2000. Their geographic information system (GIS) database included a vegetation map with eight cover types, elevation data, nest tree locations, and one random location within each nest stand. Distances to forest edge from each nest and random location were compared, and they found no evidence in their study area that California spotted owls used nest sites closer to forest edges than one would expect by chance, and this was consistent over a wide range of elevations. They also suggested that the owls in the study area nested farther from high-contrast edges than expected by chance.

Mapping Core Use Area Characteristics

The primary areas used by spotted owls for nesting and foraging (core use areas) contain the contiguous forest an owl or owl pair uses consistently, including the nest and roosting area (Blakesley et al. 2005, Williams et al. 2011). It is pointed out in chapter 3 that because these forests contain nest sites, the characteristics between territory and nest stand often overlap. When mapping large areas such as owl core use areas (e.g., territories) on the order of 150 to 400 ha (500 to 1,000 ac), moderate-resolution imagery such as Landsat (resolution 30 m [99 ft]) has had a dominant yet contested role.

Hunter et al. (1995) used Landsat imagery and landscape metrics to understand spotted owl core use areas. While they focused on the northern spotted owl (*Strix occidentals caurina*), I have discussed the paper here because of the precedent it set. They used a single date Landsat-5 TM image and classified the core use area of the northern spotted owl in Humboldt County, California, into broad vegetation life-form classes. They then compared the landscape characteristics (land cover, fragmentation, and heterogeneity) within circular areas of 800-m (2,640-ft) radius (200 ha [520 ac]) around each spotted owl nest, roost, and random sites between 1988 and 1992. Nest and roost sites were characterized by lower amounts of nonvegetation and herbaceous land cover, and by greater amounts of mature and old-growth coniferous forest, which was less fragmented than random sites. They noted that the spectral similarities in the Landsat images between structurally similar seral stages made some age classification difficult. For example, differences between mature and old-growth forests were difficult to map using these data. Moen and Gutiérrez (1997) also used classified Landsat-5 TM imagery to examine the landscape characteristics within a 457-ha [1,142-ac] area surrounding 25 owl centers. They mapped minimum convex polygons that included both roosts and nests. The Landsat-5 image was classified by dominant species, size class, and canopy closure. This paper highlighted early on one of the main challenges for wildlife researchers using Landsat imagery and products—the typically poor ability of the Landsat pixel to capture the large tree (> 60 cm [24 in] d.b.h.) component of forests that appears to be critical to the spotted owl in particular.

Numerous researchers have focused on the impact of fire on spotted owl core area habitat. In a geographically broad study, Bond et al. (2002) examined the response of all three spotted owl subspecies to wildfire in Arizona, California, and New Mexico. They examined the response of owls after large (>540-ha [1,350-ac]) wildfires occurred within their territories. Large-fire locations were derived from the Fire Resources and Assessment Program fire perimeter database, which is a statewide geodatabase with wildfire history, prescribed burns, and other fuel modification projects current through 2013, and from the USFS. These digital fire data sets were critical for the study, and they called for more large-scale experiments to understand the effects of prescribed burning on spotted owls.

Seamans and Gutiérrez (2007) modeled the probability of territory colonization, territory extinction, and breeding dispersal in relation to the amount of mature conifer forest in the central Sierra Nevada. They used an existing map of forest cover developed from aerial photographs, digital-orthophoto-quarter quadrangles, and extensive ground sampling of the forest to classify tree size class and canopy closure (Chatfield 2005) and to estimate the amount of each forest class within a 400-ha (1,000-ac) circle (radius = 1128 m [0.7-mi] or half the mean nearest neighbor distance of occupied territories in their study area averaged over the years 1990 to 2002). They found that the amount of mature conifer forest (i.e., dominated by trees ≥30.4 cm (12 in) d.b.h. with canopy cover ≥70 percent) was correlated with spotted owl occupancy. Territories with more mature conifer forest had a higher probability of being colonized and a lower probability of becoming unoccupied. They also reported that alteration of mature conifer forest appeared to decrease the probability of colonization.

Roberts et al. (2011) examined the effects of fire severity on spotted owl site occupancy in late-successional montane forest in Yosemite National Park using a relatively new burn-severity metric called the relative differenced normalized burn ratio (RdNBR) (Miller and Thode 2007). Using images of an area before and after a fire remotely sensed by Landsat bands 4 and 7, they calculated the RdNBR to create a relative measure of vegetation change, which is then classified into four levels of fire severity:

- Unburned or unchanged
- Low severity
- Moderate severity
- High severity

A polygon map of fire severity for fires in Yosemite was used to compare owl site occupancy, and the authors reported that density estimates of California spotted owl pairs were similar in burned and unburned forests. They suggested that low- to moderate-severity fires might maintain habitat characteristics essential for spotted owls, and further that managed fires that emulate the historical fire regime of these forests may help maintain spotted owl habitat and protect this species from the effects of future catastrophic fires.

Lee et al. (2013) also examined the impact of fire and disturbance on spotted owl occupancy. They mapped the 203-ha (500-ac) forested area (radius approximately 800 m [0.5 mi]) surrounding a single owl nest tree location within each owl territory before and after fires in the San Bernardino and San Jacinto Mountains of southern California to investigate the influence of fire and salvage logging on spotted owls. Spotted owl sites affected by fire were those where the perimeter of the 203-ha (500-ac) core area overlapped the perimeter of one of the fires that occurred in the area from 2003 to 2007. The prefire map was created using 1-m resolution CIR aerial photographs and stereo pairs of color aerial photographs. Imagery from NAIP taken for the San Bernardino National Forest in October 2009 was used to remap vegetation in core areas that burned between October 2003 and October 2007. They also used Google Earth imagery to estimate the amount of the 203-ha (500-ac) area affected by extensive postfire tree removal. They found that sites where high-severity fire affected >50 ha (125 ac) of forested habitat could still support spotted owls and recommended that all burned sites should be monitored for occupancy before management actions such as salvage logging were undertaken.

Other researchers have modeled fire behavior to predict future impacts of fires on spotted owl habitat. Moghaddas et al. (2010) used two common fire modeling software programs FlamMap and FARSITE that were parameterized with vegetation maps derived from IKONOS imagery, ground-based plot data, and integrated data from ARCFUELS and the Forest Vegetation Simulator. They modeled conditional burn probability under 97^{th} percentile weather conditions across Meadow Valley in the Plumas National Forest to investigate the impact of forest fuel treatments. The study area contained California spotted owl habitat areas, protected activity centers, and home range core areas. Fourteen percent of the study area was spotted owl core area. The modeled results indicated that the average conditional burn probability was reduced between pre- and posttreatment landscapes, and the stands designated for management of spotted owls as well as other resources were assumed to benefit from the landscape fuel treatments.

Mapping Characteristics of Foraging Habitat

Spotted owls forage in forests characterized by a mosaic of vegetation types and seral stages interspersed within mature forest as well as in contiguous stands of mature and old-growth forest (chapter 3). Landsat imagery was used by Lahaye et al. (2001) to classify vegetation into four categories: owl nesting and roosting habitat, owl foraging habitat, nonforested vegetation, and other non-owl habitats. They used this classification to estimate the proportion of the study area supporting owl nesting and foraging habitat in a study investigating timing and patterns of owl dispersal in the San Bernardino Mountains in southern California. This is a highly fragmented region with only 2 percent of the landscape covered by vegetation types that support spotted owls. They showed that the majority of owl dispersers settled in territories that were occupied by either pairs or single owls the previous year, some settled in vacant territories next to occupied sites, and a few settled at sites of unknown occupancy. No owls settled at unoccupied sites that were not adjacent to occupied sites.

Detailed forest habitat maps have been commonly made by private landowners and can be used in spotted owl research. For example, Irwin et al. (2007) used owl telemetry and existing vegetation maps provided by a private forestry company to evaluate owl foraging habitat. Sierra Pacific Industries inventoried their forests from August 1997 to March 1999 on an 80- by 200-m (264- by 660-ft) grid. They used this map to compare habitat values at owl and random locations within 95 percent minimum convex polygon home ranges. Results indicated that stands more likely to be chosen for foraging included those with intermediate values of the combined basal areas of three conifer species Douglas-fir (*Pseudotsuga menziesii*), white fir (*Abies concolor*), and red fir (*A. magnifica*) and greater basal area of large-diameter hardwoods. The relative probability of selection for foraging habitat decreased with increasing basal area of ponderosa pine (*Pinus ponderosa* Lawson & C. Lawson). Topographic position, habitat heterogeneity, tree species composition, and forest density also influenced foraging site selection.

In 2002, the McNally Fire burned 610 km^2 of land in the southern Sierra Nevada, including forests containing four California spotted owl territories. Four years later, Bond et al. (2009) examined effects of fire on these seven radiomarked owls from these territories by quantifying, as a function of fire severity, owl use of forests for nesting, roosting, and foraging. They used the Landsat-based EVEG vegetation map to establish habitat within foraging ranges of spotted owl and Landsat-based RdNBR to quantify fire severity. They reported that within 1 km of the center of their foraging areas, spotted owls selected all severities of burned forest and avoided unburned forest. Beyond 1.5 km of a center of foraging area, there were no discernable differences in use patterns among burn severities, and owls foraged at low rates in burned and unburned areas. Owls foraged in high-severity burned forest with greater basal area of snags and higher shrub and herbaceous cover more than in all other burn categories.

Mapping Home Ranges

Owl home ranges encompass the area used by an owl to meet its requirements for survival and reproduction (chapter 3) and are large (e.g., 600 to 2200 ha [1,500 to 5,500 ac]). Mapping owl home ranges often requires moderate-scale resolution imagery. The first use of Landsat for California spotted owl habitat research was described in Bias and Gutiérrez (1992), who used Landsat imagery to investigate spotted owl home range characteristics across ownership. They used Landsat-5 TM images from 1986 and 1987 to measure the interspersion, or rate of change, of different habitat types along 50 randomly located transect lines throughout owl territories. Their study area crossed the boundaries of the Eldorado and Tahoe National Forests, and had a mixed ownership: 60 percent was public land and 40 percent was private land. Their analysis was largely pre-digital: they superimposed the Landsat-5 images onto base maps using a stereo zoom transfer scope and interpreted vegetation changes from the Landsat images based on recognition and identification of image characteristics (i.e., tone, texture, color). They defined habitat interspersion as the number of habitat changes along a segment divided by the scale-equivalent length of that segment. This metric (habitat change per kilometer) was then compared across public land, private land, and nest sites. Ownership pattern influenced roosting and nesting behavior: the majority of observed roosts and all owl nests were on public lands.

Tempel and Gutiérrez (2002) investigated whether the environment within an owl territory might affect stress hormone levels. They collected fecal samples from spotted owls in Eldorado and Tahoe National Forests to determine if certain environmental factors were correlated with elevated fecal corticosterone levels. The environmental variables they examined were largely derived from the USFS EVEG Landsat product, and included the amount of core and edge habitat, number of habitat patches, and the total length of roads within an owl territory. While a linkage between fecal corticosterone and environment was not found, they suggested protocols for sampling corticosterone in birds. Bond et al. 2009 used both the USFS vegetation EVEG map product and the RdNBR product to understand how spotted owls were using habitat after a fire. They found that spotted owls at two areas on the Sequoia National Forest foraged in a range of burn severities, illustrating that a mosaic of burn severities in California spotted owl territories apparently allows owl use 4 years after a fire.

The accuracy of the Landsat-derived vegetation maps were explicitly tested by Hines et al. (2005) who performed a sensitivity analysis of the EVEG product developed for the USFS in southern California to estimate how mapping errors in vegetation type, forest canopy cover, and tree crown size might affect the delineation of suitable habitat for the California spotted owl. In this cautionary note on the use of existing coarse-scale land cover products, the authors reported an increase in the estimated area of suitable habitat types for the spotted owl solely resulting from map uncertainty.

High spatial resolution imagery has also been used to map forest structure and owl habitat in greater detail than possible by Landsat. Williams et al. (2011) used the USFS, NAIP imagery from 2005 to estimate tree size, canopy cover, and hardwood or conifer forest in the Eldorado and Tahoe National Forests study area. They digitized the boundaries of vegetation patches and then classified the patches into eight vegetation classes based on tree size and canopy cover consistent with the California Wildlife Habitat Relationships system (Mayer and Laudenslayer 1988). The vegetation of every owl home range in the Eldorado and Tahoe National Forests study area as well as 2,161 random locations throughout the study area was mapped and compared. They found that landscape heterogeneity (number of patches) was an important additional positive factor in owl home-range size, as well as owl foraging site selection.

Accuracy Assessment

Understanding the accuracy of a remotely sensed product is critical for determining its usefulness. I reviewed all papers assessed in this chapter for a description of accuracy, and the way in which accuracy might play a role in the use of the product. Under half (eight) of them explicitly discussed accuracy of products used. Currently, best practices for assessing and reporting accuracy of classified remotely sensed maps include the development of an "error matrix" in which reference values are checked against classified values across the types of land cover values (Congalton and Green 1999, Foody 2002). Reference data ideally should come from field data gathered contemporaneously with imagery. Because this is often difficult, many researchers use as reference data imagery at higher resolutions than the source imagery. Metrics derived from an error matrix include overall accuracy (percentage), and errors of omission (or Producer's accuracy) and errors of commission (or User's accuracy) for each land cover class mapped. These are important measures to evaluate prior to use of land cover maps as the most important classes for owl biology might be the classes that are difficult to accurately map. An additional metric—the kappa statistic—is often reported and gives the likelihood that a classification is better than random. When a remote sensing product is presented as a physical measure, such as canopy cover, its accuracy is reported using a correlation coefficient (r^2) or root-mean-square error (RMSE), which is based on regression between field-derived reference data and remotely sensed values.

Papers of several researchers I reviewed used the error matrix approach to evaluate mapped products (Chatfield 2005, Hunter et al. 1995, Phillips et al. 2010, Ripple et al. 1997, Seamans and Gutiérrez 2005, Williams et al 2011) reporting overall accuracies of mapped product from aerial photography interpretation generally above 80 percent and overall accuracies of Landsat classification at 76 percent (Hunter et al. 1995). Moen and Gutiérrez (1997) reported an accuracy of 76 percent for the Landsat habitat map, but noted that the product lacked the “residual tree” component that appears critical for owls for their use of medium-sized tree forests. Bond et al. (2009) used the error matrix approach to evaluate a burn-severity map, and found it was 93 percent correct (with 80 field validation sites).

The implication of the accuracy of the Landsat-derived vegetation maps was explicitly examined by Hines et al. (2005), who performed a sensitivity analysis of the EVEG product developed for the USFS in southern California to estimate how mapping errors in vegetation type, forest canopy cover, and tree crown size might affect the delineation of suitable habitat for the California spotted owl. They reported the overall accuracy for USFS Landsat-derived vegetation map was 73 percent, but individual class accuracy ranged from 25 to 100 percent. They used these error values in a simulation experiment to evaluate the role of mapped error in over or underpredicting owl habitat. In this cautionary note on the use of existing coarse-scale land cover products, the authors reported an increase in the estimated area of suitable habitat types for the spotted owl solely resulting from map uncertainty.

Accuracy assessment of LiDAR mapped products is more complicated than for optical imagery. Hyde et al. (2005) evaluated LiDAR-derived canopy height measures using regression between field and LiDAR canopy height measures and reported high r^2 and low RMSE. The positional accuracy of LiDAR-derived locations of individual trees requires taking a sample of tree locations in the field using high-quality GPS, and reporting the RMSE in x and y directions between reference and LiDAR. This is often not done owing to the difficulties in gathering sufficient samples in the field. García-Feced et al. (2011) compared in general terms the number and pattern of residual trees and canopy cover in the area surrounding four nest trees between LiDAR and field-derived values and show concordance of LiDAR with field sampling.

Chapter Summary

Mapping technology has been critical to understanding the ways owls use their forest habitat and to help manage forests for their sustainability. Many studies have relied on moderate-resolution Landsat imagery to map large areas of forest, but this is not without challenges. Of primary importance is the assessment of accuracy in mapped products. Despite the need to understand product quality, the accuracy of mapped products is not routinely evaluated. Fewer than half of the articles I reviewed included a description of any accuracy assessment. Recommended accuracy assessment approaches are not universally adopted in the remote sensing community (Foody 2002). Remotely sensed or GIS-derived products are often used as predictor variables in regression models without consideration of uncertainty. This is problematic as traditional regression-based statistical models assume that the covariates are measured without error when this is never the case. Additionally, although the overall accuracies of mapped products reviewed here were generally high (greater than 75 percent), individual class accuracies vary considerably, and can be quite low. Also of importance is the difficulty of optical remote sensing to capture much of the structural elements so critical to owls (e.g., high concentrations of large trees, multilayered canopy).

We can expect that new developments in high-resolution, multitemporal imagery, and particularly in active remote sensing methods such as LiDAR, will play increasing roles in wildlife research and management as their costs decrease. These tools provide more detail about the horizontal and vertical structure of forests, and when linked to accurate and often dynamic measures of animal location, a richer understanding of the use of the forest by these species can be developed. Yet despite great improvements in mapping provided by LiDAR and other high-resolution sensors, there are considerable outstanding needs for mapping of wildlife habitat. First, there is a need to better map important wildlife habitat elements within forests such as snags and large broken-top trees, which may be important to many wildlife species, including the spotted owl (Gutiérrez et al. 1992). Currently, remote sensors map these structural elements indirectly based on the vertical heterogeneity of the forest canopy (e.g., Martinuzzi et al. 2009), but they remain difficult to estimate accurately, particularly in dense forests (Blanchard et al. 2011). Second, research is ongoing to develop better metrics of vertical canopy structure for assessing habitat. Analysis of the discrete return point cloud can produce hundreds of structural and physics-based metrics (e.g., coefficient of variation of hits, or vertical distribution of hits), but many of these cannot be field verified, and they lack any management meaning. Simpler metrics that can be linked to management goals and ascertained in the field are needed. Synergies between ground-based LiDAR and airborne

LiDAR data might help to improve the characterization of vertical structure (e.g., Henning and Radtke 2006, Iavarone 2005). Third, species classification needs to be improved, particularly in mixed forests. The integration of LiDAR with other optical imagery (at fine and coarse resolutions) are proving very useful in mapping forests with increased species discrimination, as well as providing information on stress and biomass (Asner and Mascaro 2014, Gonzalez et al. 2010, Ke et al. 2010, Swatantran et al. 2011). Finally, optical and LiDAR fusion might also help to scale important forest structural measurements such as heterogeneity over spatial scales that are commensurate with owl home ranges (e.g., Chopping et al. 2012). These developments will likely augment the ways in which we map wildlife habitat in the near future.

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