LiDAR as a Tool to Characterize Wildlife Habitat: California Spotted Owl Nesting Habitat as an Example

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We show the use of an emerging technology, airborne light detection and ranging (LiDAR), to assess forest wildlife habitat by showing how it can improve the characterization of California spotted owl (Strix occidentalis occidentalis) nesting habitat. Large residual trees are important elements for many wildlife species and often, apparently, facilitate selection of habitat by spotted owls. However, we currently lack the ability to identify such trees over large spatial scales. We acquired multiple-return, high-resolution LiDAR data for a 107.1-km$^2$ area in the central Sierra Nevada, California. We surveyed for spotted owls within this area during 2007–2009 and located four nest trees. We then used the LiDAR data to measure the number, density, and pattern of residual trees (≥90-cm dbh) and to estimate canopy cover within 200 m of four nest trees. Nest trees were surrounded by large numbers of residual trees and high canopy cover. We believe that LiDAR would greatly benefit forest managers and scientists in the assessment of wildlife–habitat relationships and conservation of important wildlife species.

Keywords: California spotted owl, canopy cover, LiDAR, nesting habitat, residual trees, Strix occidentalis occidentalis, Sierra Nevada

Forest managers and scientists often require data on habitat conditions over large areas to assess wildlife–habitat relationships and effectively manage and conserve focal wildlife species. However, habitat characteristics are often inferred from field data of limited spatial extent or are assessed using remote sensing techniques (e.g., aerial photographs and satellite images) that do not characterize vertical structure (Vierling et al. 2008, Seavy et al. 2009). Traditional optical remote sensing technologies may also lack the resolution to identify critical structural elements for some wildlife species. For example, residual large trees within younger forests are difficult to quantify over large spatial scales but provide critical habitat for species typically associated with older forests or dependent on such large trees (Hunter and Bond 2001). We believe the identification of residual trees, trees that could possibly serve as nest trees, at large spatial scales would greatly improve our ability to manage species that rely on them.

Recently, airborne light detection and ranging (LiDAR) has emerged as a technology that can fill this need. LiDAR has been used in some wildlife habitat studies, but its use has been much more limited relative to other remote sensing techniques (Lefsky et al. 2002b, Hyde et al. 2005, Vierling et al. 2008, Seavy et al. 2009, Selvarajan et al. 2009, Wing et al. 2010). Airborne LiDAR uses laser technology such that a LiDAR instrument is mounted on an aircraft and emits laser pulses during flight that strike the target surface below the aircraft. A portion of the laser energy is reflected by the ground or surface objects (e.g., vegetation and buildings) and detected by a sensor in the LiDAR instrument. The roundtrip time for each pulse is measured, allowing the instrument to calculate the distance to the ground or object. Simultaneously, the aircraft’s exact position and orientation are recorded by an onboard global positioning system (GPS).
and inertial measurement unit (Figure 1). From these data, one can calculate the three-dimensional position of the surface that reflected the laser pulse (Dubayah and Drake 2000, Lefsky et al. 2002a, 2002b, Reutebuch et al. 2005, Roth et al. 2007, Vierling et al. 2008). LiDAR data can be captured from aircraft (and soon satellite)-mounted instruments (airborne LiDAR) or from ground-based systems (ground-based LiDAR). Airborne LiDAR covers more area than ground-based LiDAR but with less detail. Airborne LiDAR data are classified based on whether they record the range to the first or last return (single return), or multiple returns, or fully digitize the return signal (waveform LiDAR), and whether they have a small (typically a few centimeters) or large (tens of meters) “footprint” (laser illumination area) (Dubayah and Drake 2000).

Another important aspect of airborne LiDAR data is its point density, usually defined as the number of points per unit area. Point density depends on the aircraft’s distance above the ground, the sampling rate, and the scanning pattern (Dubayah and Drake 2000). Higher point densities can be obtained by flying closer to the ground, but the aircraft must stay in the air longer to cover the same surface area, which significantly increases the acquisition costs. LiDAR data are delivered as a “point cloud”—a collection of \( x \), \( y \), and \( z \)-values and their corresponding intensities (maximum return) that can be projected in three-dimensional space.

Typically, the first step in analysis is to derive a bare earth, or digital terrain model (DTM), where elevation is referenced to a common vertical datum. These high-resolution DTMs have proven to be very accurate in depicting topography (Reutebuch et al. 2003, Hodgson et al. 2005). From each value in the point cloud, the bare earth elevation is subtracted, yielding a point cloud of canopy heights. Stand-level attributes can be estimated using these data, such as basal area, canopy cover, vertical structure, and forest biomass (Lefsky et al. 2001, Popescu et al. 2003, Zimble et al. 2003, Hudak et al. 2006), but the next step for LiDAR data collected in wooded areas is typically the extraction of individual tree data (Chen et al. 2006) and then the estimation of individual tree attributes such as tree height, stem density, and crown diameter (Lefsky et al. 2001, Naesset and Bjerknes 2001, Popescu et al. 2003, Andersen et al. 2006, Falkowski et al. 2006). In terms of accuracy, Wing et al. (2010) did not detect significant differences between field-based and LiDAR-derived tree horizontal positions within a forested area in southwestern Oregon. Furthermore, Andersen et al. (2006) found that, although field methods yield slightly more accurate tree height measurements than LiDAR, this difference is likely to be offset by the increased cost efficiency and the wider coverage of LiDAR-based forest surveys.

We used multiple-return, small-footprint airborne LiDAR data to characterize forest structure in the area immediately surrounding California spotted owl (Strix occidentalis occidentalis) nest trees in the central Sierra Nevada. The spotted owl is a focal management species in the Sierra Nevada because it is associated with late-seral forests for roosting and nesting habitat (Gutiérrez et al. 1992, US Forest Service 2004). In addition, previous research conducted near our study site showed that spotted owls in this region select nest and roost sites characterized by large trees and high canopy cover (Bias and Gutiérrez 1992, Moen and Gutiérrez 1997, Bond et al. 2004). Of particular importance, vegetation maps derived from Landsat data and air photographs by the US Forest Service have failed to detect the residual tree component within younger forests near our study area; residual trees may facilitate use of younger forests by owls as nesting or roosting habitat (Moen and Gutiérrez 1997). We believe that LiDAR could be used to identify such trees and, more generally, to assess spotted owl nesting habitat over large spatial scales. As an initial step in this effort, we showed the use of LiDAR to quantify residual trees and canopy cover within 200 m of owl nest sites. Because of a small sample size (four nest trees), we did not compare owl nesting and nonnesting habitat.

**Study Area**

Our study area encompassed 107.1 km\(^2\) on the Tahoe National Forest in the

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**Figure 1. Demonstration of multiple-return LiDAR technology.** The height of an object can be calculated based on the elapsed time between an emitted pulse and its return. Image modified from Lefsky et al. (2002b).
central Sierra Nevada, approximately 30 km east of Foresthill, California (Figure 2), and was the site of the Sierra Nevada Adaptive Management Project, a multidisciplinary study on the ecological and social effects of forest fuels treatments (Sierra Nevada Adaptive Management Project 2011). Maximum elevation of the study area was 2,000 m. The vegetation was primarily mixed-conifer forest containing ponderosa pine (*Pinus ponderosa*), sugar pine (*Pinus lambertiana*), white fir (*Abies concolor*), Douglas fir (*Pseudotsuga menziesii*), red fir (*Abies magnifica*), incense cedar (*Calocedrus decurrens*), and black oak (*Quercus kelloggii*). Portions of the study area consisted of chaparral and bare rock.

**Methods**

**Field Data Collection**

**Spotted Owl Surveys.** We surveyed for spotted owls during the breeding season (April–August) from 2007 to 2009. We systematically established a set of survey points throughout the study area based on historic owl locations, local topography, and road access. We then conducted 10-minute surveys at night from these points. If an owl was detected on a nighttime survey, we located it during the day to assess reproductive status and locate nest trees following established protocols (Franklin et al. 1996). We recorded locations of nest trees using a Garmin 60CSx GPS unit (Garmin, Ltd., Olathe, KS). Four of these nest trees were located within our LiDAR data footprint, and we used the locations of these trees in the subsequent analysis. The nest trees were located at four spotted owl territories that we referred to as GREEK, LASTC, OAKFL, and SWCAN.

**Vegetation Data.** We collected vegetation data around three nest trees in August 2010 for comparison with the LiDAR estimates of residual tree density and canopy cover. We did not collect field data at the OAKFL site because of steep terrain and dense brush. We recorded the number and species of all trees ≥90-cm dbh within 100 m of a nest tree. In addition, we established four transects at a nest tree for estimating canopy cover; transects began at the nest tree and extended 100 m in each cardinal direction. We then used a densitometer to record the presence or absence of canopy cover directly overhead at 1-m intervals along each transect.

**LiDAR Data and Analysis**

We contracted with the National Center for Airborne LiDAR Mapping (National Center for Airborne Laser Mapping 2011) to collect small-footprint, multiple-return airborne LiDAR data of our area in September 2008. The aircraft was flown at 600 m aboveground level. Data were collected using an Optech GEMINI Airborne Laser Terrain Mapper with the following technical specifications: four range measurements per pulse, a pulse rate frequency of 70 kHz, a laser wavelength of 1,047 nm, and a point density of 9 points/m². The accuracy of these data was estimated using over 1,000 check points surveyed with vehicle-mounted GPS over the study area. Vertical accuracy is reported as 0.05 m (5 cm), and horizontal error is reported at 0.01 m (1 cm; standard errors). The data were delivered in tiled LAS (the LAS file format is a public file format for the interchange of three-dimensional point cloud data between data users format).

Only the tiles that comprised the forests surrounding each owl nest tree were selected and processed. We used a software module designed for LiDAR data built into ENVI software (ITT Visual Information Solutions) to separate the data into ground and aboveground points. We generated a 0.25-m resolution raster digital surface model (DSM; equivalent to the top surface of the canopy) using the aboveground points and a 0.25-m resolution raster DTM (Optech, Inc., Rochester, NY) using the ground points. We then applied a spatial median filter (kernel size of 5) to both the DSM and the DTM to obtain the height difference between the two raster grids. This vertical distance produced our canopy height model (CHM). We extracted individual trees from the CHM using TreeVaW software (Kini and Popescu 2004), which used the programming language International Data Language (IDL). This software identifies and locates trees by using a “filtering window” of varying size that searches for the local maximum value within the window. The filtering window maximum size...
was based on tree height, which was derived from the CHM. We chose 5 m as the minimum expected crown width to ensure that we captured large trees. The output from TreeVaW was a text file that included the location, the height, and the crown radius of each detected tree. We converted the text file to an ArcGIS shapefile. We then established two circles of different radii (100 and 200 m) around spotted owl nest trees using ArcGIS software (ESRI, Inc., Redlands, CA).

We defined a residual tree as being ≥90-cm dbh in the field. This cutoff had been previously used by Bias and Gutiérrez (1992) and LaHaye and Gutiérrez (1999). To identify these residual trees from among all trees in the LiDAR data set, we modeled the relationship between dbh and tree height using field data collected from 355 sample plots (0.05 ha, 12.62-m radius) before LiDAR acquisition. Based on our field experience, we estimated the probability that trees of three different minimum heights (35, 40, and 45 m) were residual trees. Trees in the three height classes had a 77, 92, and 95% probability, respectively, of being a residual tree. We first considered any tree ≥45 m high in the LiDAR data set to be a residual tree. This initial run resulted in overestimation and underestimation of residual trees at two sites (LASTC and GREEK) when compared with the residual tree counts from the 100-m field plots. We suspected that these discrepancies were because of differences in forest composition at the sites (e.g., LASTC contained proportionally more sugar pine and GREEK contained more white fir). We found that we needed to slightly vary the height threshold for these two sites, based on their different species composition. Thus, we used a threshold of 47.5 m in LASTC and of 40 m in GREEK. We estimated canopy cover from the CHM by considering any 0.25-m pixel having a minimum height ≥9 m to be part of the canopy layer.

Within each concentric ring (i.e., 0–100 m from the nest tree and 100–200 m from the nest tree), we calculated the following habitat variables using ArcGIS: the number of residual trees, the density of residual trees (number of trees per hectare), the clustering of the residual trees, the largest arc central angle of the residual trees (defined as that angle formed by two lines drawn from the nest tree that bounds the largest section of the ring containing no residual trees), and the percent canopy cover (Figure 3). We used Ripley’s K statistic (Ripley 1976, 1981), a second-order, spatial-point pattern analytical technique that tests for spatial randomness (Ripley 1976, Kenkel 1988, 1994, Cressie 1993), to measure the clustering of residual trees. We developed confidence envelopes for interpreting clustering using 100 random iterations.

**Results**

Results were consistent among sites with respect to number and pattern of residual trees and canopy cover in the area surrounding the nest tree. The number of residual trees and the density of residual trees in the area surrounding each nest tree were high, ranging from 123 to 222 trees/ha and 9 to 17 trees/ha, respectively (Table 1; Figure 4). With the exception of SWCAN, the residual trees surrounding the center nest tree were clustered at a range of scales (Figure 5). Canopy cover was uniformly high around all the nest trees, ranging from 50 to 80% in the rings surrounding the four nest trees (Table 1). Our LiDAR-based estimates agreed closely with residual tree counts and canopy cover estimates based on field data collected within 100 m of three nest trees (Table 1).

**Discussion**

**Spotted Owl Nesting Habitat**

We used spotted owl nesting habitat as an example to illustrate the power of LiDAR for assessing forest habitat characteristics relevant to wildlife. Inference to spotted owl habitat must be made cautiously because of our small sample size. However, the ability to detect and, more importantly, quantify both the number and the spatial arrangement of residual trees using LiDAR data provided a more rigorous assessment of spotted owl habitat than other remote sensing techniques (e.g., aerial photographs and satellite images) and provided there is LiDAR coverage that coincides with existing monitored nest trees, the processing time required to map additional nest trees in this manner is minimal. It could also help resolve the longstanding quandary of observations of spotted owls in some younger forests (Gutiérrez et al. 1992, Moen and Gutiérrez 1997).

Each nest tree was located in forests...
having a high concentration of residual trees and dense canopy cover, which was consistent with previous research on owl nesting habitat (Bias and Gutierrez 1992, LaHaye et al. 1997, Moen and Gutierrez 1997, LaHaye and Gutierrez 1999, North et al. 2000). The pattern of the residual trees surrounding the nest tree was generally clustered, which may indicate that owls were benefiting from the microclimate provided by the clumped trees. Conversely, residual trees on our study area may simply occur in clusters much of the time.

**General Applicability of LiDAR to Forest Wildlife Studies**

In addition to the spotted owl, other species of management concern rely on the largest trees within a forested habitat. For example, the red-cockaded woodpecker (*Picoides borealis*) selects the oldest trees within southeastern US pine forests for nest cavity excavation (Rudolph and Conner 1991), a relationship that may be driven by the increased incidence of red heart fungus (*Phellinus pini*) on older trees. The fisher (*Martes pennanti*) in the Sierra Nevada uses larger trees for resting sites, which are thought to be the limiting habitat element for this forest mustelid (Purcell et al. 2009). Thus, the management of these and similar species could benefit greatly from the use of LiDAR data to quantify the occurrence of large trees on the landscape.

Vertical habitat structure has long been recognized to have a major influence on animal diversity and abundance (MacArthur and MacArthur 1961, James 1971). Vertical structure is also an important habitat characteristic for individual species, such as the spotted owl and fisher (Gutierrez et al. 1992, Purcell et al. 2009). Unfortunately, quantifying vertical structure over large spatial scales based solely on field data is impractical because of the labor-intensive nature of field data collection. Airborne LiDAR has great potential to characterize vertical structure of nest sites over large areas (e.g., Müller et al. 2010).

**Future Research Needs**

We are aware of a few recent wildlife habitat studies that quantify vertical structure using LiDAR data. For example, Goetz et al. (2007) used large footprint (12 m) airborne LiDAR data to calculate an index of vertical structure that greatly enhanced their

### Table 1. The number of residual trees extracted from LiDAR data with various height thresholds, density of residual trees (number per hectare), canopy cover (%), and largest arc central angle between residual trees within concentric rings of two different radii around four California spotted owl nest trees in the central Sierra Nevada, 2007–2009.

<table>
<thead>
<tr>
<th>Radius (m)</th>
<th>Tree</th>
<th>LiDAR</th>
<th>No. of residual trees</th>
<th>Density of residual trees (no. RT/ha)</th>
<th>Canopy cover (%)</th>
<th>Largest arc central angle between residual trees (°)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>100</td>
<td>200</td>
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<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>GREEK (h &gt; 40 m)</td>
<td>58</td>
<td>52</td>
<td>164</td>
<td>222</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>SWCAN (h &gt; 45 m)</td>
<td>50</td>
<td>46</td>
<td>154</td>
<td>204</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>OAKFL (h &gt; 45 m)</td>
<td>39</td>
<td>NA</td>
<td>84</td>
<td>123</td>
<td></td>
</tr>
<tr>
<td>100</td>
<td>LASTC (h &gt; 47.5 m)</td>
<td>70</td>
<td>71</td>
<td>139</td>
<td>209</td>
<td></td>
</tr>
<tr>
<td>200</td>
<td>GREEK (h &gt; 40 m)</td>
<td>18.46</td>
<td>16.6</td>
<td>17.40</td>
<td>17.67</td>
<td></td>
</tr>
<tr>
<td>200</td>
<td>SWCAN (h &gt; 45 m)</td>
<td>15.92</td>
<td>14.6</td>
<td>16.34</td>
<td>16.23</td>
<td></td>
</tr>
<tr>
<td>200</td>
<td>OAKFL (h &gt; 45 m)</td>
<td>12.41</td>
<td>NA</td>
<td>8.91</td>
<td>9.79</td>
<td></td>
</tr>
<tr>
<td>200</td>
<td>LASTC (h &gt; 47.5 m)</td>
<td>22.28</td>
<td>22.6</td>
<td>14.75</td>
<td>16.63</td>
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</tr>
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<td>Entire area</td>
<td>GREEK (h &gt; 40 m)</td>
<td>63.68</td>
<td>67.0</td>
<td>59.96</td>
<td>61.43</td>
<td></td>
</tr>
<tr>
<td>Entire area</td>
<td>SWCAN (h &gt; 45 m)</td>
<td>72.11</td>
<td>70.0</td>
<td>69.43</td>
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<tr>
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<td>65.24</td>
<td>69.08</td>
<td></td>
</tr>
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</table>

For three of our sites, we provide field data from surveys within the 100-m buffer; trees >90-cm dbh were included as residual trees. We used multiple-return LiDAR data to identify residual trees and estimate canopy cover.
habitat models for predicting avian species richness. Seavy et al. (2009) used small footprint LiDAR (<1 m) to describe habitat associations of riparian passerine birds. They calculated the mean and coefficient of variation of canopy height at a number of spatial scales and linked those metrics with avian occupancy. Müller et al. (2010) used high density discrete LiDAR (derived from waveform LiDAR) to investigate the relative importance of vegetation physiognomy and plant species composition in predicting the composition of bird assemblages in Germany. They examined mean canopy height, the SD of mean, canopy height, and the maximum height of canopy calculated from the digital crown model, and found that these structural factors better predicted bird assemblages than field data alone.

These three cases show the usefulness of LiDAR in characterizing wildlife habitat; however, additional research using different kinds of LiDAR is needed to develop and identify meaningful measures of vertical canopy structure for assessing wildlife habitat. In such studies, additional selective sampling with ground-based LiDAR could supplement the airborne LiDAR data to improve the characterization of vertical structure (Iavarone 2005, Henning and Radtke 2006). Additionally, the integration of LiDAR with other optical imagery will be important for species classification as well as forest composition (Ke et al. 2010).

We currently lack sufficient knowledge about the capability of LiDAR to identify other important wildlife habitat elements within forests such as large broken-top trees and snags. Large broken-top trees may be important to many wildlife species, such as spotted owls (Gutiérrez et al. 1992). However, our height-based method for identifying residual trees would likely miss many of the large broken-top trees within a forest. Likewise, snags are important habitat elements for many wildlife species but may be difficult to identify using airborne LiDAR. Nevertheless, Martinuzzi et al. (2009) pointed out that the value of LiDAR data resided in the ability to quantify structural metrics that are known to directly or indirectly indicate the presence of snags such as the vertical heterogeneity of the forest canopy.

Management Implications

We believe that LiDAR offers great potential to improve the ability of forest managers and scientists to conserve key wildlife

Figure 5. Ripley’s K results for four spotted owl nest trees. The observed K (solid gray line) is above the confidence envelope (dashed line) when clustering is present and within the confidence envelope when the pattern is random. The black arrow indicates the scale at which clustering of residual trees is largest.
species by enhancing habitat assessments. For example, the US Forest Service in the Sierra Nevada has identified the spotted owl, fisher, and northern goshawk (Accipiter gentilis) as focal management species but has also committed itself to the implementation of widespread forest-thinning treatments to reduce wildfire risk (US Forest Service 2004). These projects have the potential to impact the focal wildlife species by removing some larger trees (≥76-cm dbh) and simplifying the understory. Here and elsewhere, the US Forest Service could use LiDAR-derived habitat data to better anticipate the impacts of proposed management actions on wildlife, meet the requirements of major environmental laws (e.g., the Endangered Species Act), and defend its actions against potential litigation (Malmheimer et al. 2004).

However, LiDAR technology has important drawbacks. LiDAR data can be expensive to acquire, and considerable expertise is required to process the raw data (Dubayah and Drake 2000). Currently, there is no single or standard LiDAR processing software. Fortunately, LiDAR costs decrease substantially as the area sampled increases (Tilley et al. 2005, Hudak et al. 2008). LiDAR costs could be mitigated by shared acquisition among different agencies, both state and federal, that would benefit from the LiDAR data. In addition, there are several planned satellite missions specifically designed to collect LiDAR data for forest structure (i.e., NASA’s DESDyne; Freeman et al. 2009). Finally, data processing could be contracted with private firms or universities until agencies develop the capacity to process LiDAR data. Given these considerations, we believe that LiDAR is a technology that could greatly benefit land-management agencies and advocate for increased use of LiDAR for wildlife habitat assessment.

Literature Cited


June, 2011.


