Characterizing habitats associated with fisher den structures in the Southern Sierra Nevada, California using discrete return lidar

F. Zhao\textsuperscript{a}, R.A. Sweitzer\textsuperscript{a}, Q. Guo\textsuperscript{b}, M. Kelly\textsuperscript{a,c,*}

\textsuperscript{a} Department of Environmental Science, Policy and Management, University of California, Berkeley, CA 94720, USA
\textsuperscript{b} School of Engineering, University of California, Merced, CA, USA
\textsuperscript{c} Geospatial Innovation Facility, University of California, Berkeley, CA, USA

\begin{abstract}
Lidar data provide information on the vertical and horizontal structure of forests, and lidar remote sensing can be effective in characterizing the forest habitats of mammals. This study explored the ability of lidar-derived metrics to capture topography and forest structure surrounding denning trees used by the Pacific fisher (Martes pennanti) as a case study to illustrate the utility of lidar remote sensing in studying mammal-habitat associations. Lidar data were collected in September 2007 across conifer dominated forests in the Sierra Nevada Mountains that include a full range of forest density. We used Classification and Regression Trees (CART) to statistically compare the slope and lidar-derived forest height and structure metrics in the circular area (with radius of 10–50 m) surrounding denning trees and randomly selected non-denning trees. We accessed our model accuracy using resubstitution and cross-validation methods. Our results show that there is a strong association between fisher denning activity and its surrounding forested environment across scales, with high classification accuracy (overall accuracies above 80% and cross-validation accuracies above 70%) at 20, 30 and 50 m ranges. The best classification accuracies were found at 20 m (optimal resubstitution accuracy 86.2% and cross-validation accuracy 78%). Tree height and slope were important variables in classifying the area immediately surrounding denning trees; at scales larger than 20 m, forest structure and complexity became more important. The variables identified were also consistent with those identified from previous studies describing fisher resting tree structure. Based on these findings, we conclude that lidar remote sensing has utility in forest characterization for fishers and has great potential for mammal studies.
\end{abstract}

\section{1. Introduction}

Fishers (Martes pennanti) are a medium-size mammal carnivore with a pre-European distribution encompassing the boreal forest zone of Canada, the Great Lakes region and northeastern United States, a relatively limited portion of the Rocky Mountains in the United States, and in mountainous areas of Washington, Oregon and California (Gibilisco, 1994). The range of fishers in the Pacific states is now greatly reduced primarily due to commercial trapping (late 1800s to mid 1900s), changes to forest structure associated with logging and altered fire regimes, increased human access (e.g., roadkill), and habitat loss associated with urban and recreational development (Powell and Ziehnski, 1994; Purcell et al., 2009; Zielinski et al., 2005, 2010). Fishers in California are now limited to approximately 47% of their early 1900 range (Zielinski et al., 1995), and populations in this region have been designated a Distinct Population Segment and are a candidate species under the Federal Endangered Species Act (Federal Register, 2004). The fisher had been considered a candidate species under the California Endangered Species Act until 2010, and is currently a candidate species of special concern in this state. Nevertheless, fishers in California now exist as two genetically isolated populations (northern California and the southern Sierra Nevada; Davis et al., 2007; Knaus et al., 2011), and a recent estimate noted that there may be fewer than 350 total animals in the southern Sierra Nevada population (Spencer et al., 2011). Because of continued concern over the limited abundance and range extent of this species in western North America, several major studies are underway aimed at identifying population limiting factors, general habitat associations, and specific habitat requirements for resting and reproduction (Purcell et al., 2009; Zielinski et al., 2010).

Resting and denning structures are considered to be the most important habitat elements required for maintenance of fisher populations (Lofroth et al., 2010; Weir et al., 2012). Fishers exhibit the greatest selection for natal dens and resting sites and the least for foraging locations (Kelly, 1977; Burnett, 1981; Arthur et al., 1989;...
Jones and Garton, 1994; Powell and Zielinski, 1994; Zielinski et al., 2006). Most of the relevant literature has concentrated on identification and analysis of resting sites, which are typically structures (trees or snags) used as protection from predators and inclement weather and as a way to regulate body temperature (Powell and Zielinski, 1994). Multiple previous efforts have focused on identifying resting habitat used by fishers by measuring habitat characteristics around known rest structures; resting sites are most often associated with high canopy cover, large trees and snags, forest structural complexity, relatively close proximity to water in or near drainages, and on steep slopes (Seglund, 1995; Zielinski et al., 2004, 2005, 2006; Yaeger, 2005; Purcell et al., 2009). Much less is currently known about fisher reproductive den structures and their associated habitats, especially within the West Coast Distinct Population Segment in the western United States.

The locations and habitat associations for fisher den structures are similar but not identical to areas used for resting (Spencer et al., unpublished data). In the southern Sierra Nevada and at a large spatial scale, fishers selected den trees from a narrower range of biotic and abiotic conditions than habitats used for other activities; a combined analysis of 184 known den trees indicated that den structures were closely associated with densely forested stands including a moderately high proportion of hardwoods (Quercus kelloggii), and at relatively lower elevations than predicted by a more general habitat model (Spencer et al., unpublished data). The actual den structures used by fishers in western North America are typically among the largest DBH trees and snags in the immediate area around the actual tree or snag (Lofroth et al., 2010; Weir et al., 2012). Biologists conducting ongoing research at four different areas within the West Coast Distinct Population Segment are all collecting detailed data on habitats around den trees within 12-m to 18-m radius circular plots centered on den trees.

As an augmentation to field data, remotely sensed data has been widely adopted to characterize habitat heterogeneity across a range of scales. As an addition to optical remote sensing, lidar remote sensing can characterize the 3-dimensional structure of forest habitat with a variety of physically meaningful metrics (Goetz et al., 2007) such as canopy cover, biomass, canopy height profile, and subcanopy topography. Lidar remote sensing has showed its utility in understanding the association between vegetation structure and biodiversity, particularly with birds (e.g., the black-throated blue warbler). Bergen et al. (2009) reported that one third of previous wildlife research using remotely sensed data focused on birds (Goetz et al., 2007, 2010; Bergen et al., 2009; Garcia-Feced et al., 2011) because many bird species have forest structural preferences. However, the utility of lidar remote sensing to improve the understanding between vegetation structure and mammal species remain little known.

In this paper, we explored the utility of a small footprint discrete return lidar remote sensing data to assess the denning habitat of fishers in the Sierra Nevada. Our objectives were to: (1) identify lidar-derived variables that separate fisher denning structure from random trees, and (2) test the utility of lidar data to assess fisher denning habitat structure across scales from immediately surrounding each tree to 50 m away from a tree.

2. Materials and methods

2.1. Study area

The study area (“Sugar Pine”) is located northeast of Oakhurst, California, and covers approximately 36.1 km² (Fig. 1). This area is topographically complex with elevations ranging from 758 m to 2852 m. Primary tree species in the order of abundance include Calocedrus decurrens (incense cedar), Abies concolor (white fir), Pinus ponderosa (ponderosa pine), Pinus lambertiana (sugar pine), Sequoiodendro giganteum (giant sequoia), Quercus kelloggii (black oak), Quercus spp. (live oak), Cornus nuttallii (mountain dogwood) and Ainus rhombifolia (white alder). Of all the species, conifers comprise 89.57%; the remaining 10% deciduous species are primarily black oak and live oak. The forest is mixed, and species composition among plots may vary significantly.

The study area is part of a larger adaptive management program called SNAMP, the Sierra Nevada Adaptive Management Project, which was formed to evaluate the impact of strategically placed forest fuel treatments on wildlife (specifically the California Spotted Owl and the Pacific Fisher), water quality and quantity, forest health and fire prevention.

2.2. Trapping and radiotelemetry

Individual female fishers were captured in live traps that were placed in appropriate locations near camera survey stations where fishers had been previously detected by automatic digital cameras (RECONYX Inc., Holmen, WI). Extensive camera-based surveys for fishers were conducted annually in the region encompassing the Sugar Pine study area each year from October 2007 to September 2011 in association with a larger study of the biology of fishers in the area. Live-trapping was focused during the fall and winter seasons when fishers were captured in steel mesh traps (Tomahawk Live Trap Company, Tomahawk, WI) modified to include a plywood cubby box to provide shelter (Seglund, 1995). Live traps were checked daily by late morning, and captured animals were transferred to and restrained in a handling cone, and sedated using a mixture of Ketamine hydrochloride and Diazepam (1 mg Diazepam/200 mg Ketamine) injected intramuscularly. Sedated fishers were weighed, classified by age and sex based on examination of teeth and genitalia, and measured for a variety of standard morphological features. Each animal was fitted with a radiocollar (Holohil Systems Model MI-2M, Ontario, Canada; Advanced Telemetry Systems Model 1930 or 1940, Isanti, MN), and also received a subcutaneous passive integrated transponder (PIT) tag (Biomark, Boise, ID) for permanent and unique identification. All radiocollared fishers were subsequently monitored for survival status and relocated four to 6 days/week by fixed-wing airplane following standard techniques described by Thompson et al. (in press). All capture and handling procedures were in compliance with guidelines of the American Society of Mammalogists (Gannon et al., 2007), completed under permit from CA Department of Fish and Game, and approved by our University of California Berkeley Animal Use Protocol (#R139).

2.3. Fisher denning plots

At the start of each denning season in late March we relocated all subadult and adult-aged female fishers multiple times over successive days during early morning telemetry flights to identify evidence of spatial clustering (three to five locations within 500 m). Potential denning structures were subsequently identified by navigating to Universal Transverse Mercator (UTM) coordinates for location clusters using handheld Global Positioning System devices (Garmin model 60 Cx; Olathe, KS), and homing towards telemetry signals to identify trees or snags occupied by radiocollared fishers. Whenever female fishers were localized to a tree or snag within a location cluster, two to four automatic digital cameras were then attached to nearby trees and focused on the bole of the den structure. Trees and snags that were used ≥ 3 times
by adult female fishers (Paragi et al., 1996) and with images indicating up/down movements were considered denning structures. The procedure for monitoring fisher den trees was specifically designed to minimize disturbance to denning females when they are known to be in den trees.

Female fishers will typically transfer young kits from structures in which they were born (natal dens) to one to four or more other trees or snags (maternal dens) during the April to early June denning season (Paragi et al., 1996). Each time we had evidence that a reproductive female fisher had moved kits (cessation of use of a den structure based on lack of images, failure to locate the female in the den structure over multiple days, or images of the female transporting kits away from the den tree), we searched for the female using ground telemetry and homing, and repositioned cameras to focus them on the next maternal den structure. This process of relocating female fishers in successive den trees was repeated until the end of the denning season when females were no longer localizing to den structures (typically early to mid June). A combined 28 natal and maternal den trees were identified in the Sugar Pine area during 2008, 2009, 2010, and 2011. Locations of trees or snags that were confirmed as den trees were recorded as the average of a minimum of 50 point estimates using a Garmin 60CSs handheld GPS. On average, the accuracy of locations (n = 28) recorded for den trees/snags used for lidar analyses was 4.45 ± SE 0.24 m (range 2.7–8.0 m).

2.4. Fisher random tree plots

A total of 121 0.05-ha plots were inventoried. Each plot covered an area with 12.62 m radius around an accurately located plot center (Collins et al., 2011). The first plot was randomly chosen and the following plots were placed on a 500 m grid. When a plot was less than 12.62 m from landing or road surface, it was moved 25 m in a randomly chosen cardinal direction. Within each plot we located, measured and recorded forest structural attributes, including species, diameter at breast height, tree height and height to base of live crown. The plot was also photographed from four vantage points. From the 121 random plots sampled, we dropped seven plots within a range of 200 m of an identified fisher denning plot and then randomly selected 28 plots from the remaining 114 plots to match fisher denning sites. It is noted that in this study these 28 plots were used only to provide the geographic location for extracting lidar metrics.

2.5. Airborne lidar data processing

Lidar data was collected in September 2007 using an Optech GEMINI Airborne Terrain Mapper (ALTM) mounted in a twin-engine Cessna Skymaster in our study area. The ALTM emits pulses of near-infrared light (1047 nm) at a rate of 100 kHz. A maximum of four returns were recorded for each pulse. The mean point density within our study area can reach a maximum of 12 points per m². The point clouds were classified into two classes: ground returns and aboveground returns by the National Center for Airborne Laser Mapping (NCALM). The Digital Terrain Model (DTM) was generated using the classified ground point and has a spatial resolution of 1-m (Guo et al., 2010). The height of aboveground returns is computed by subtracting the DTM to remove the terrain effects on the vertical distribution of aboveground returns.
2.5.1. Lidar metrics derived from point clouds

All returns corresponding to each plot were clipped from the lidar dataset and several groups of variables were derived from the height distribution of canopy returns. To avoid the inclusion of ground returns, a 1 m threshold was used to eliminate returns close to the ground. Height metrics were divided into four groups: statistical metrics, canopy height percentiles metrics, canopy transmittance metrics, and foliage profile metrics (Tables 1 and 2). Statistical metrics include maximum, mean, standard deviation, kurtosis, skewness, coefficient of variation (CV). Canopy percentile metrics are calculated from the 10th percentile through the 90th percentile in 10% increments. Canopy transmittance metrics are the ratio of returns at each canopy percentile height over the total number of returns. We also calculated the slope of the ground at each scale from the DEM.

Lovell et al. (2003) described the methodology to derive an apparent foliage profile from a small footprint lidar. The gap probability from the top to a given height, \( z \), is estimated by the following equations:

\[
P_{\text{gap}} = 1 - \left( \frac{\#z_j | z_j > z}{N} \right) \quad (1)
\]

\[
L(z) = -\log(P_{\text{gap}}(z)) \quad (2)
\]

where \( \#z \) is the number of hits down to a height \( z \) above the ground and \( N \) is the total number of independent lidar shots. The apparent foliage profile is then given by Eq. (2). To test the utility of apparent foliage profile in biomass, three metrics were selected: maximum foliage area volume density, height of maximum foliage volume density and distance between top of the apparent foliage profile and height at maximum foliage volume density. Maximum foliage area density reflects the foliage density condition for trees with a specified region, and height of maximum foliage volume density is the height where trees have the maximum foliage density. The distance between top of the apparent foliage profile and height of maximum FAVD could be indicative of the pattern of foliage in the upper crown.

Ni-Meister et al. (2010) reported that wood volume is a good predictor of plot level biomass, particularly for conifer forests. To produce volumetric lidar metrics, we built an empirical relationship from the collected field data using the DBH and tree height for all measured trees (a total of 1248 trees) in our study area. The equation is as follows:

\[
DBH = 4.37 + 1.81 \times HT
\]

Fig. 2 illustrates that in general, the DBH of trees in our study area correlates well with height, suggesting that this simplified correlation can be indicative of tree volume. Because lidar only provides height related metrics, and there are no lidar metrics available directly related to basal area, in this study we integrated the simplified relationship between DBH and height into the canopy percentile height metrics, and produce volumetric metrics. For example, for height at \( P_{10} \), the volumetric metric is:

\[
V_{10} = P_{10} \times (P_{10} \times \text{Eq. (5)})^2
\]

2.5.2. Tree-level metrics derived from individual trees

In addition to the lidar metrics above, we also calculated a suite of "tree-level" metrics based on individual trees derived from the lidar point cloud. A variety of methods are available for isolating individual trees from lidar data (e.g. Popescu et al., 2003; Hyde et al., 2007; Persson et al., 2002; Kwak et al., 2007). To extract individual trees from point clouds, we followed a newly developed

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Metrics derived from the height distribution of the lidar data.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Label</td>
<td>Description</td>
</tr>
<tr>
<td>Max ht</td>
<td>Maximum height</td>
</tr>
<tr>
<td>Mean ht</td>
<td>Mean of heights</td>
</tr>
<tr>
<td>Std ht</td>
<td>Standard deviation of heights</td>
</tr>
<tr>
<td>Skew ht</td>
<td>Skewness of heights</td>
</tr>
<tr>
<td>Kur ht</td>
<td>Kurtosis of heights</td>
</tr>
<tr>
<td>CV ht</td>
<td>Coefficient of heights</td>
</tr>
<tr>
<td>QMCH</td>
<td>Quadratic mean of height</td>
</tr>
<tr>
<td>Canopy cover</td>
<td>Transmittance at 1 m above ground</td>
</tr>
<tr>
<td>Max fp</td>
<td>Maximum foliage profile density</td>
</tr>
<tr>
<td>Max fp height</td>
<td>Height at Max fp</td>
</tr>
<tr>
<td>Top Max fp height</td>
<td>Distance between tree top and the height at Max fp</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 2</th>
<th>Variables selected by optimal trees at 10–50 m range.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Radius (m)</td>
<td>Variables selected</td>
</tr>
<tr>
<td>10</td>
<td>Maximum height, slope</td>
</tr>
<tr>
<td>20</td>
<td>Standard deviation of heights, slope</td>
</tr>
<tr>
<td>30</td>
<td>Standard deviation of heights, Kurtosis of heights, slope</td>
</tr>
<tr>
<td>40</td>
<td>Standard deviation of heights, slope</td>
</tr>
<tr>
<td>50</td>
<td>Mean of heights, transmittance at 10th percentile heights, Canopy cover</td>
</tr>
</tbody>
</table>

Fig. 2. The general relationship between DBH and tree height at the single tree level.

\[
Y = 4.37 + 1.81 \times X
\]

\[
R^2 = 0.71
\]

\[
\text{RMSE} = 13.75
\]
method developed by Li and colleagues (2012), which has been tested in the mixed conifer trees in Sierras and showed outstanding performance. After the height and canopy radius were derived, statistics (e.g., mean height, skewness of heights of all individual trees with a plot) based on individual trees were calculated (Table 2). Although both sets of lidar metrics (tree-level metrics derived

![Fig. 3. Optimal CART tree for the presence/absence classification. Presence = 1, absence = 0. The number of plots assigned to 0 (on the left) and 1 (on the right) is indicated below each end node. Here canopy_c and Ind_mean represent canopy cover and mean heights of individual trees.](image)

<table>
<thead>
<tr>
<th>CART</th>
<th>Number of samples</th>
<th>Accuracy (%)</th>
<th>Resubstitution accuracy (%)</th>
<th>Cross-validation accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Absence</td>
<td>Presence</td>
<td>Absence</td>
<td>Presence</td>
<td></td>
</tr>
<tr>
<td>10 m</td>
<td>23</td>
<td>5</td>
<td>82.2</td>
<td>78.6</td>
</tr>
<tr>
<td>Absence</td>
<td>7</td>
<td>21</td>
<td>75</td>
<td></td>
</tr>
<tr>
<td>20 m</td>
<td>25</td>
<td>3</td>
<td>89.3</td>
<td>86.2</td>
</tr>
<tr>
<td>Absence</td>
<td>5</td>
<td>23</td>
<td>82.2</td>
<td></td>
</tr>
<tr>
<td>30 m</td>
<td>23</td>
<td>5</td>
<td>82.2</td>
<td>83.9</td>
</tr>
<tr>
<td>Absence</td>
<td>4</td>
<td>24</td>
<td>85.7</td>
<td></td>
</tr>
<tr>
<td>40 m</td>
<td>22</td>
<td>6</td>
<td>78.5</td>
<td>76.8</td>
</tr>
<tr>
<td>Absence</td>
<td>7</td>
<td>21</td>
<td>75.0</td>
<td></td>
</tr>
<tr>
<td>50 m</td>
<td>20</td>
<td>8</td>
<td>71.47</td>
<td>82.1</td>
</tr>
<tr>
<td>Absence</td>
<td>2</td>
<td>26</td>
<td>92.9</td>
<td></td>
</tr>
</tbody>
</table>
from individual trees, and lidar metrics derived directly from the lidar point cloud) are retrieved at plot level, they differ in one aspect. Tree-level metrics derived from the individual trees treat each individual tree as independent elements, and thus the resultant metrics are analogous to conventional plot-level metrics derived from field inventory data. In contrast, lidar metrics derived from the lidar point cloud directly treat the lidar point cloud as a whole; consequently, larger trees are given more weight because larger trees intercept more laser energy. As a result, these two groups of metrics are not identical, and provide complementary information with respect to the forest habitat structure. All metrics were calculated using MatLab software.

2.6. Classification and Regression Trees (CART) model

A variety of statistical models were available to explore the relationship between presence/absence of denning trees and lidar-derived metrics, including stepwise multiple linear regression (MLR), generalized additive models (GAM), and CART. Goetz et al. (2007) tested the aforementioned statistic models to predict bird species richness in an eastern temperate forest, USA, and reported that they all produced similar results. However, he noted an advantage the CART method was that it displays the amount of variation for each variable (Goetz et al., 2007). De’ath and Fabricus (2000) also reported that classification and regression trees are ideally suited for the analysis of complex ecological data because the method has the flexibility to handle a broad range of response types, it is invariant to monotonic transformations of the explanatory variables, it is easy to construct and interpret, and it has the ability to handle missing values in both response and explanatory variables. As a result, we chose CART to evaluate the utility of a small footprint lidar system to predict the distribution of denning trees in our study area.

CART is a nonparametric technique which builds classification and regression trees for predicting either continuous variables (regression) and categorical predictor variables (classification) (Breiman et al., 1984). It iteratively splits the dataset in two groups based on discriminative rules that minimize a user-specified loss function. Each split of the data is known as a node, and thus form a tree structure. After the tree is fully developed, it needs to be pruned according to a cost-complexity rule. A tuning parameter (e.g. cp values) is selected so that it minimizes the cross-validation error.

In this study, CART models were selected to predict the presence and absence of denning trees based on the lidar metrics retrieved from 28 fisher denning plots and 28 random denning tree absence plots. The CART trees provided lidar-derived variables that indicate the hypothesized relationship between fisher denning activity and the surrounding environment. The analysis was conducted using the rpart library (Therneau and Atkinson, 1997) in the statistical package R, version 2.2.0 (R development core Team, 2006). As a response variable, the presence and absence of denning trees for 56 plots were coded as “1” and “0” respectively.

To compare the performance of CART models, two criteria were used: resubstitution accuracy and 10-fold cross-validation accuracy. Resubstitution accuracy represents the correspondence between the response training data and the predictions of the response based on the input training data. High response resubstitution accuracy does not guarantee good prediction for new data, and resubstitution accuracy can result in over-optimistic estimates of accuracy. To counter this problem, we also implemented a 10-fold cross validation, which splits the training data into 10 parts randomly. In each model run, nine parts of the data are used for training and the tenth part is used to examine the predictive accuracy for each new tree. This method gives a better test of the predictive power of the resulting tree because it tests the trees with new data, other than training data.

2.7. Plot size

Plot size may matter in studying the association between fisher denning tree and the lidar metrics derived because lidar metrics derived at one scale may not be sufficient to predict habit selection at another scale. As a result, studies conducted at multiple scales may provide a more comprehensive characterization of habitat use pattern than those conducted at single scale (Poizat and Pont, 1996). In addition, fishers may select different habitat attributes at different scales. In this analysis we compared CART models from a range of plot sizes. To identify the plot size that best characterizes the denning and random tree structure, we characterized the sites at ranges with radius varying from 10-m to 50-m, centered on a denning or non-denning tree.

3. Results

Classification tree analysis was run at five ranges; the lidar metrics selected for each model are listed in Table 2. Fig. 3 shows the optimal CART trees for the presence/absence classification for each range. In general, the optimal CART tree contained two or three variables from both the lidar point cloud-based metrics and the individual tree-based metrics. Table 3 shows the confusion matrix, resubstitution accuracy and 10-fold cross validation accuracy for each model across scales.

At the 10-m range, the most important CART tree split was maximum height, suggesting that denning site was distinguished by the presence by tall trees. The second split indicates that denning trees were generally located on steep slopes. The regression tree at range 10-m had a resubstitution accuracy of 78.6% and a cross-validation accuracy of 66.0%. Maximum height (Max_ht) within the 10-m range may be influenced by the denning trees themselves, and may indicate that the denning structure needs to be sufficiently large in diameter to supply denning cavities. The two equations combined (Max_ht > 33-m and slope > 17) suggested that trees growing in comparatively steep slope were desired by fishers for rearing kits.

The optimal CART tree at the 20-m range produced the highest resubstitution accuracy (86.2%) and the highest cross-validation accuracy (78.0%). Variables predicting fisher denning sites at the 20-m range differed slightly from those at the 10-m range. Slope remained one of the two variables selected, but the standard deviation of heights (Std_ht) became important in the tree at the 20-m range. The high standard deviation of heights suggested that denning sites were structurally more complex than random sites.

At the 30-m range, the kurtosis of individual tree composition was found to be effective in model performance, in addition to slope and standard deviation of heights. This newly added variable shows a high value for denning trees, indicating a peak distribution of taller trees. This finding may indicate that denning trees are located in large tree clusters, and rarely stand alone with many relatively small trees. The variables identified, resubstitution accuracy and cross-validation accuracy in 40-m range are quite similar to those at 30-m range.

As the range increased to 50 m, the mean height of individual trees, transmittance at 10th percentile height and canopy cover contributed to the optimal CART tree produced. Both canopy cover and transmittance at 10th percentile height are related to the canopy cover characteristic. These three variables combined indicated that at this range, denning trees were strongly associated with larger mature trees with high canopy cover.

4. Discussion

Our analyses of lidar derived habitat variables indicated that tree height, slope, and forest structure were strongly correlated...
with fisher denning tree location. The literature also suggests that in addition to metrics derived directly from lidar data, other geographic conditions are also correlated with core fisher habitat, such as proximity to water (Zielsinski et al., 2004; Carroll, 2005). We did not investigate these additional variables because we were mainly interested in the areas immediately surrounding each denning tree. This may lead to an understimation of the utility of lidar remote sensing to study fisher denning tree selection. Similarly, logs and large snags have been reported as a preferred place for denning (Paragi et al., 1996; Weir et al., 2012). Although there are some research efforts that attempt to distinguish between live and dead standing tree biomass and to map snags on the ground (Kim et al., 2009; Martinuzzi et al., 2009; Blanchard et al., 2011), snags and log information were not taken into account in this work due to the limited ability of airborne lidar to accurately capture information on understory snags and logs (Blanchard et al., 2011). Moreover, fisher may have preference for specific species of trees related to the dynamics of cavity formation (Weir et al., 2012), and integrating species information may also be helpful to better predict the association between fisher denning tree distribution.

The selected variables, resubstitution accuracy and 10 cross-fold validation accuracy were not equivalent across spatial scales. The explanatory power of habitat variables peaked at the 20-m range. The mechanisms for the optimal spatial scale are not yet clear, but one possible explanation is that there were fewer trees included within the 10-m range in this mature forest. Thus, lidar-metrics derived at this scale might reflect the information of denning trees and random trees themselves. In contrast, lidar metrics derived from the 20 to 50 m scales include information from the surrounding environment. Thus, the maximum height provided an excellent explanatory power at 10-m scale while in other scales, structural complexity metrics (e.g., standard deviation of height or mean heights) showed superior explanatory power. Also lower resubstitution accuracy and cross fold validation accuracy at 10-m range indicated that the surrounding environment, rather than denning tree itself, might determine the denning tree selection of fishers.

Related to this, our analysis suggested that habitats associated with denning structures used by fishers were structurally more complex than random sites, likely related to higher vertical structural diversity. In addition, small openings may encourage the development of shrubs that typically contribute to the diversity of potential food items. In general, structurally diverse forests are known to support higher species diversity (Hansen et al., 1991), including more abundant ground-dwelling rodents and tree squirrels (Paillet et al., 2009; Manning et al., 2012). This is important for female fishers because they are constrained in their movements during the denning season by the need to periodically return to den structures to wean and provision dependent offspring. We hypothesize that female fishers may select den trees in areas with more structurally diverse forests because those habitats support more abundant prey needed to support the energetic costs of lactation. Fishers in the region encompassing our study area consume tree squirrels, small rodents, birds, and small lizards (Zielsinski et al., 1999; Zielsinski and Duncan, 2004). Data on availability of these types of prey are not known for our study area, but would be very useful for understanding where fishers choose to den on the forest landscape.

As lidar data are generally costly, this study was limited in both space and time. The lidar data were collected once on a limited coverage of 36.1 km². However, both spatial and temporal scales are certainly expected to influence fisher denning tree selection. As a result, the influence of spatial and temporal scales cannot be addressed with the limited data currently available, but could be a focus of future research.

The spatial extents (i.e., 10–50 m) we selected were arbitrary. This approach is useful for making hypotheses, but may not be able to reveal the true mechanism behind the selection of denning trees by fishers. Future planned analyses will use information on size of fisher home ranges and kernel-based utilization distributions to investigate how forest habitat structure varies between core use areas around den structures compared to within the 90% and 95% isopleths.

5. Conclusions

In this case study, we tested the utility of metrics derived from discrete return, small footprint lidar in distinguishing between trees used by the Pacific fisher for denning, and non-denning trees in the Sierra National Forest, CA. Our main findings are as follows:

1. Discrete return lidar-derived variables proved useful for characterizing the forest habitat conditions surrounding trees and snags used by the Pacific fisher for reproduction.

2. The CART algorithm demonstrated advantages in classification, such as the flexibility to handle a broad range of response types, invariance to monotonic transformations of the explanatory variables, ease and robustness of construction, and ease of interpretation in forest habitat studies.

3. Large trees and snags used by fishers as denning structures were associated with forestsed areas with relatively high canopy cover, large trees, and high levels of vertical structural diversity. Den structures were also located on steeper slopes, potentially associated with drainages with streams or access to water.

4. We hypothesize that the types of structurally complex forest habitats occupied by denning female fishers provided access to an abundance and diversity of prey required for successful reproduction.

5. It should be noted that this study was limited in both space and time, and to generalize our findings to larger scale will require further exploration of a larger area over a longer term.

The use of airborne lidar system in studying the association between fisher denning activity and forest habitat has not been conducted in the past. This research has important implications for the use of lidar remote sensing to improve the characterization of forest habitats for mammals.

References


119


