Burned forest characterization at single-tree level with Airborne Laser Scanning for assessing wildlife habitat

Ángeles Casas¹, Mariano García^{2,3}, Rodney B. Siegel⁴, Alexander Koltunov^{1,5}, Carlos Ramírez⁵, and Susan Ustin¹

¹*Department of Land, Air and Water Resources, One Shields Avenue,
University of California, Davis, USA*

²*University of Leicester, Centre for Landscape and Climate Research,
University Road, Leicester, LE1 7RH, UK*

³*Jet Propulsion Laboratory, California Institute of Technology,
Pasadena, CA 91109, USA*

⁴*The Institute for Bird Populations, Point Reyes Station, California,
USA*

⁵*USDA Forest Service, Region 5 Remote Sensing Lab, McClellan,
California, USA*

Abstract

Abundance, size, and spatial distribution of standing dead trees (snags), are key indicators of forest biodiversity and ecosystem health. These metrics represent critical habitat components for various wildlife species of conservation concern, including the Black-backed Woodpecker (*Picoides arcticus*), which is strongly associated with

recently burned conifer forest. We assessed the potential of Airborne Laser Scanning (ALS) to detect and characterize conifer snags and identify Black-backed Woodpecker habitat using previously derived empirical thresholds of conifer snag basal area. Over the footprint of the Rim Fire, a megafire that extended ($\sim 104,000$ ha) through a heterogeneous mosaic of conifer forests, oak woodlands, and meadows in the Sierra Nevada mountains of California, we identified conifer snags and estimated their basal area from single-tree ALS-derived metrics using Gaussian processes in four major steps. First, individual trees were mapped using the Watershed Segmentation algorithm, resulting in 87% detection of trees with stem diameter larger than 30 cm. Second, the snag/live classification model identified snags with an overall accuracy of 91.8 %, using the coefficient of variation of height and intensity together with maximum intensity and fractional cover as the most relevant metrics. Third, the conifer/hardwood snag classification model utilizing the maximum height, median height, minimum intensity, and area metrics separated snag forest types with an overall accuracy of 84.8 %. Finally, a Gaussian process regression model reliably estimated conifer snag stem diameter ($R^2 = 0.81$) using height and crown area, thus significantly outperforming regionally calibrated conifer-specific allometric equations. As a result, $\sim 80\%$ of the snag basal area have been mapped. Optimal and potential habitat for Black-backed Woodpecker comprise 53.7 km^2 and 58.4 km^2 , respectively, representing 5.1 and 5.6% of the footprint of the Rim Fire. Our study illustrates the utility of high-density ALS data for characterizing recently burned forests, which, in conjunction with information about the habitat needs of particular snag-dependent wildlife species, can be used to assess habitat characteristics, and thus contribute

greatly to forest management and biodiversity conservation.

Keywords: Gaussian Processes, Watershed Segmentation, Single-tree level, Stem Diameter, Basal Area, Megafire, Wildlife Habitat, Black-backed Woodpecker, Airborne Laser Scanning, LiDAR, Snags, Dead trees, Rim Fire.

1 Introduction

Standing dead trees (snags) are key indicators of forest biodiversity and ecosystem health (Siitonen, 2001; Noss et al., 2006; Moritz et al., 2014). They constitute a critical component of habitat for many rare and specialized wildlife species (Siitonen, 2001; Bütler et al., 2004). The lack of spatially distributed data on snag abundances, types, and distributions has been identified as a major constraint on the predictive capacity of occupancy and distribution models for snag-dependent wildlife species, including woodpeckers (Bütler et al., 2004; Martinuzzi et al., 2009; Müller and Bütler, 2010; Vogeler et al., 2014; Tingley et al., 2014, 2015). Woodpeckers fulfill a keystone function in conifer forests as primary cavity excavators whose cavities are subsequently used by numerous other species for roosting, nesting, and concealment from predators (Daily et al., 1993; Tarbill et al., 2015). Increasing size and frequency of forest fires in temperate forests resulting from climate change (Flannigan et al., 2009; Miller et al., 2009; Stephens et al., 2013) will only exacerbate the need for detailed, accurate mapping of snags in burned areas to inform decisions about post-fire forest management and biodiversity conservation.

Since the key role of forest physiognomy in wildlife habitat was established (MacArthur and MacArthur, 1961) it has been used to explain species occurrence and overall diversity (Farley et al., 1994). Airborne Laser Scanning (ALS) capability to characterize detailed vertical and horizontal structural patterns across broad areas has been successfully applied to advance wildlife habitat modeling (Mason et al., 2003) and assess wildlife-habitat relationships (Davenport et al., 2000; Bradbury et al., 2005).

23 On the one hand, ALS data can be used as an exploratory tool to better understand
24 resource selection by species of known distributions (Goetz et al., 2007; Clawges
25 et al., 2008; Smart et al., 2012; Garabedian et al., 2014; Ackers et al., 2015). How-
26 ever, ALS data also can be used to delineate habitat suitability, through mapping of
27 habitat features known to be important for target species (Mason et al., 2003; Nelson
28 et al., 2005; Hyde et al., 2006; Swatantran et al., 2008; Martinuzzi et al., 2009; Graf
29 et al., 2009). Basal area, which is closely related to biomass (Bergen et al., 2009) is
30 a common measure of tree cover used in wildlife habitat studies (Cade, 1997). While
31 not directly measured by ALS, basal area can be derived from ALS data. Although
32 often critical for predicting or assessing habitat suitability for wildlife, stem diameter
33 and basal area are not generally available at the landscape scale. This is particularly
34 troublesome in the case of burned forests where wildlife occupancy and habitat rela-
35 tionships for snag-dependent wildlife species are commonly defined as a function of
36 snag basal area (Martinuzzi et al., 2009; Tingley et al., 2014).

37 In recent years, some studies have attempted to use ALS in relation to dead or
38 dying trees for applications such as estimation of dead biomass or carbon storage
39 (Kim et al., 2009; Ferster et al., 2009), forest health or successional stage estimation
40 (Bater et al., 2009; Bright et al., 2013), and wildlife habitat studies (Martinuzzi et al.,
41 2009). A relation between ALS-derived height metrics and dead trees has been found
42 using a plot-based approach with varying results (Solberg et al., 2006; Sherrill et al.,
43 2008; Pesonen et al., 2009; Bater et al., 2009; Martinuzzi et al., 2009), whereas other
44 studies have shown LiDAR intensity data provides an effective predictor of dead
45 trees (Kim et al., 2009; Hudak et al., 2012; Bright et al., 2013). At the single-tree

level, the use of intensity has been explored in ALS with discrete returns (Korpela et al., 2010; Wing et al., 2015) and full-waveform (Yao et al., 2012). Korpela et al. (2010) show that dead, defoliated trees have approximately 40-60% lower intensity than living trees. Kim et al. (2009) used plot-based density distributions of intensity values rescaled to 8-bit (0-255) in a mixed coniferous forest and interpreted the lower peak in the bimodal distribution as the presence of snags. With a single-tree approach, Yao et al. (2012) successfully identified snags in a mixed mountain forest using full waveform ALS with 73% and 71% of overall accuracy for leaf-on and leaf-off condition, respectively. Interestingly, their intensity metrics were shown to be irrelevant for discrimination of dead and live trees; instead the outer geometry of the crown was found to be relevant (Yao et al., 2012). Recently, Wing et al. (2015) presented a point-wise snag filtering algorithm based on point location attributes, neighborhood intensity values, and point density statistics. In that method, tree segmentation and characterization was only applied to points that were first classified as snag points. Also, the method was applied to forests with different conditions, and therefore snag detection rates depended on snag size (Wing et al., 2015).

While the estimation of the stem diameter using ALS is a field of active research given its relation with biomass, growth, tree volume, and biodiversity factors (Popescu and Hauglin, 2014; Maltamo and Gobakken, 2014), only a few studies have attempted to estimate stem diameter and/or basal area of dead trees using a plot-based approach (Pesonen et al., 2008, 2009; Martinuzzi et al., 2009; Bright et al., 2013). Pesonen et al. (2008, 2009) first attempted to estimate standing dead wood with poor results. Bright et al. (2013) predicted dead basal area and % dead basal area in different

69 coniferous forests affected by beetle infestation with limited success. Martinuzzi
70 et al. (2009) successfully characterized the forest structure in terms of percentage of
71 snags and DBH classes known to be relevant for various wildlife species to delineate
72 patterns of wildlife habitat suitability in a mixed-conifer forest. Their study makes
73 use of heights and topographic data to derive area-based DBH classes at a 20 m pixel
74 resolution, showing important improvements when supplementary forest successional
75 data are used (Martinuzzi et al., 2009). Nevertheless, despite the importance of snags
76 in forest management and biodiversity conservation, little attention has been paid
77 to the detection and characterization of snags using ALS data for habitat mapping
78 applications (Martinuzzi et al., 2009; Vogeler et al., 2014, 2015). We know of no
79 previous example of individual snag detection and characterization (type and size)
80 using ALS data to map potential habitat for snag-dependent wildlife species.

81 This study explores the use of ALS for characterizing burned forest in relevant terms
82 for predicting wildlife habitat quality on the Rim Fire, a megafire that took place in
83 2013 in the Sierra Nevada mountains of California, creating large patches of medium-
84 and high-severity burned forest. To illustrate the utility of ALS-derived snag char-
85 acterization for forest planners and wildlife managers, we apply it to map potential
86 and optimal habitat across the fire footprint for Black-backed Woodpecker (*Picoides*
87 *arcticus*). This species has been designated by the US Forest Service as a Manage-
88 ment Indicator Species (MIS) for snags in recently burned forest across ten National
89 Forests in California. Retaining adequate habitat for this species has been a con-
90 tentious issue in post-fire forest management efforts at the Rim Fire and other recent
91 fires across the Sierra Nevada region. Black-backed Woodpecker populations in Cal-

ifornia, Oregon, and the Black Hills of South Dakota are also currently under review for federal listing as threatened or endangered. Our objective is to evaluate the use of ALS data:

1. to map individual conifer snag characteristics (type and size) across a recently burned forest, and
2. to identify patches of potential habitat for a wildlife species known to be dependent on those characteristics.

2 Methodology

2.1 Study site

The study site comprises the footprint of the 2013 Rim Fire, which burned $\sim 104,000$ ha across portions of Yosemite National Park, Stanislaus National Forest, and adjacent private lands in the Sierra Nevada Mountains of California (Figure 2). The area is topographically complex, with elevations ranging from 60 to 2400 m. The fire burned through a mosaic of vegetation types, including low-elevation (1000 - 1500 m) grasslands, chaparral, and foothill-oak woodland habitat, mainly blue oak (*Quercus douglasii* Hook. & Arn) and interior live oak (*Quercus wislizeni* A. DC. (Fagaceae)); and in the lower montane zone through conifer forests dominated by ponderosa pine (*Pinus ponderosa* Lawson and C. Lawson). Mixed conifer forests dominate the mid elevation (1500 - 2100 m), including Douglas fir (*Pseudotsuga menziesii* (Mirb.)

111 Franco), incense cedar (*Calocedrus decurrens* (Torr.) Florin), ponderosa pine (*Pinus ponderosa* Lawson and C. Lawson), sugar pine (*Pinus lambertiana* Douglas) and
 112
 113 Sierra white fir (*Abies concolor* (Gord. & Glend.) Lindl. ex Hildebr. var. lowiana
 114 (Gord. & Glend.) Lemmon), Jeffrey pine (*Pinus jeffreyi* Balf) and California black
 115 oak (*Quercus kelloggii* Newberry). White fir, red fir (*Abies magnifica* A. Murr.),
 116 western whitebark pine (*Pinus albicaulis*), and limber pine (*Pinus flexilis*) occur in
 117 higher elevation (≥ 2100 m) portions of the affected area.

118 **2.2 Black-backed Woodpecker habitat assessment**

119 We identified and classified Black-backed Woodpecker habitat based on information
 120 provided by Tingley et al. (2014), who used radio-telemetry to delineate Black-backed
 121 Woodpecker habitat home ranges in three other recently burned forest areas in Cali-
 122 fornia, and then described habitat attributes across those home ranges. Tingley et al.
 123 (2014) found that the primary driver of home-range size, and, by extension, density
 124 of Black-backed Woodpecker pairs across the landscape, was average basal area of
 125 conifer snags. Among individual woodpeckers whose home ranges were primarily
 126 or entirely within burned areas, the lowest observed value for average snag basal
 127 area across the home range was $17.4 \text{ m}^2/\text{ha}$, and the mean value was $25.5 \text{ m}^2/\text{ha}$.
 128 We consider these thresholds the best available criteria for indicating potential and
 129 optimal Black-backed Woodpecker habitat, respectively, within our study area.

130 2.3 Field plot data

131 We stratified plot locations by forest structure, status (dead/live), and type (hard-
132 wood/conifer) within the Rim Fire and an additional 2 km unburned buffer zone
133 where ALS data were available. To stratify, we used a Landsat-based pre-fire vege-
134 tation map (CALVEG www.fs.fed.us) and a burn severity map provided by the U.S.
135 Forest Service (Figure 2). We assessed 147 10-m radius field plots in October 2014;
136 80 plots were within the footprint of the Rim Fire and 65 plots were within the 2
137 km buffer (Figure 2). For every tree with a stem diameter ≥ 10 cm, we recorded
138 status, species, location, and stem diameter and height. Field plot center positions
139 were measured using differential GPS and corrections were applied using the clos-
140 est fixed antenna for position accuracy, which varied from 0.10 cm to 0.5 m. Each
141 tree was located by its distance and bearing to center of the plot. For each plot,
142 we calculated basal area, (BA, m^2/ha), number of trees per plot (N), and basal
143 area-weighted mean tree diameter, ($D_{bw,cm}$). BA (m^2/ha) was estimated as the
144 cross-sectional area of an individual tree at breast height (1.3 m above the ground)
145 and D_{bw} as $\sum_{j=1}^N (BA_j \cdot DBH_j) / \sum (BA_j)$. The basal area of plots ranged from 2.8
146 to $162 m^2/ha$ with a mean of $47.7 m^2/ha$. The minimum and maximum number of
147 trees per plot was 1 and 81 respectively, with a mean of 14. Overall, we measured
148 2067 trees, out of which 917 were alive with DBH values ranging from 10 to 155.8 cm,
149 and 1149 were dead with DBH ranging from 10 to 163.2 cm. In addition, the mean
150 DBH and standard deviation for measured conifer and hardwood snags were $29 \pm$
151 17 and 28.3 ± 19.1 respectively, with small trees outnumbering larger ones. Within
152 conifers snags, there were 657 snags with DBH between 10 and 30 cm, 240 snags

153 with DBH between 30 and 60 cm and 88 snags with DBH larger than 60 cm.

154 **2.4 Overview**

155 The data analysis workflow consisted of several steps, presented in Figure 1. First, we
156 isolated individual trees using the Watershed Segmentation algorithm initialized with
157 local maxima of the canopy height surface (Sect. 2.6). For each detected tree, we then
158 derived a group of ALS metrics used in the subsequent steps (Sect. 2.7). Then, trees
159 were classified into snags/live categories using a Gaussian processes-based algorithm
160 and the derived metrics (Sect. 2.8.2). Next, we applied the same Gaussian process
161 classifier to separate conifer from hardwood snags as discussed in Section 2.8.2. In
162 the last step, we estimated the stem diameter and basal area of the detected conifer
163 snags, using a Gaussian process-regression model (Sect. 2.8.1). Conifer snag basal
164 area estimation combined with thresholds obtained from a telemetry study of Black-
165 backed Woodpeckers in burned forest (Tingley et al. 2014) enabled the habitat
166 mapping as described in Sections 2.2.

167 **2.5 ALS data acquisition and preprocessing**

168 ALS data were collected in November 2013 by the National Center for Airborne
169 Laser Mapping (NCALM) using an Optech Gemini Airborne Laser Terrain Mapper
170 (ALTM) instrument that recorded up to four returns per pulse. The collected data
171 covered the fire burn area plus a 2-km buffer, with a scan angle of $\pm 14^\circ$ and a nominal
172 50% overlap between flight lines, yielding an average pulse density of 19 per m^2 . We

173 normalized heights with the 1-m resolution digital elevation model (DEM) developed
 174 by NCALM. In addition to the height information, the intensity was also recorded.
 175 Intensity is the ratio of power returned to power emitted (Kaasalainen et al., 2007).
 176 The instrument operates in the near infrared region at a wavelength of 1064 nm, and
 177 therefore the return intensity provides information about object properties related
 178 to the reflectivity at this wavelength. However, it is also function of the illuminated
 179 area of the object, scattering from the target, incident angle, proportion of the pulse
 180 remaining after previous returns, but primarily the sensor-target distance, or range
 181 (Brandtberg, 2007; Höfle et al., 2008; Korpela et al., 2010). Therefore, intensity
 182 necessitates a range normalization that provides the intensity values that would
 183 have been recorded if all the points were at the same range, i.e. eliminates path
 184 length variations (Holmgren and Persson, 2004). We used the normalization method,
 185 detailed in García et al. (2010), based on the following equation: $I_n = I \cdot R^2 \cdot R_s^{-2}$,
 186 where I_n is the normalized intensity, I is the original intensity, R is the range and
 187 R_s is a user-defined standard range, in our case 1000 m.

188 **2.6 Tree detection**

189 As shown in Figure 1, the tree detection consists of two main steps. First, the ALS
 190 points are converted into a smoothed canopy height model (CHM) with pixel size 0.5
 191 m, which is a sufficiently high resolution to represent the canopy variability. Second,
 192 the CHM surface is segmented into regions representing individual trees. To generate
 193 a Canopy Height Model (CHM), we used normalized ALS heights from all returns

194 and found the maximum height within a radius of the pixel size multiplied by the
195 square root of two. This radius was applied instead of the pixel size to reduce the size
196 of gaps in the initial CHM. We further applied a one-iteration anisotropic diffusion
197 filter (Perona and Malik, 1990) to smooth the CHM while preserving the edges, a
198 critical step to avoid merging canopy crowns in the filtering process. One iteration
199 was chosen to retain the height variability in the CHM while smoothing the crown.
200 To identify individual trees in the second step, we applied a local maxima detection to
201 the smoothed CHM by searching in eight-connected neighborhood pixels with higher
202 values than their external boundary neighbors. These are considered the tops of po-
203 tential trees. Then, we applied the Watershed Segmentation algorithm (Beucher and
204 Lantuéjoul, 1979) upon the inverted smoothed CHM using local maxima previously
205 detected as initial seeds. The output of the segmentation is a raster with a unique
206 tree label. At this point, segments with maximum heights less than four meters
207 were eliminated, which were considered as maxima of understory or trees with stem
208 diameters smaller than 10 cm, for which we were not interested. This relation was
209 estimated from Sierra Nevada site specific height-DBH allometric equations (Keyser
210 and Dixon, 2008). Given the low accuracy of the positioning, we used field-corrected
211 references to verify the algorithm performance. The adjustment was applied when
212 the ALS-detected tree and the field location were within a distance of 3 m and differ-
213 ences in height were less than 1 m. To evaluate tree detection, we segregated the test
214 trees into three stem diameter classes given the Black-backed Woodpecker preference
215 for medium to large snags (Dudley et al., 2012; Rota et al., 2014) for foraging, and
216 the lower contribution of small trees to estimated basal area. Following the Califor-

217 nia Wildlife Habitat Relationships (www.dfg.ca.gov/biogeodata/cwhr/), we defined:
218 small for DBH between 10 and 30 cm, medium for those between 30 and 60 cm and
219 large for DBH larger than 60 cm.

220 **2.7 ALS metrics**

For each tree segmented, ALS points higher than two meters were extracted, considering that lower points represent understory, and segments with less than ten points were eliminated. Twenty-five metrics were calculated using normalized heights and intensities (Table 1) for each tree, categorized by height, intensity, crown shape, and porosity. In addition, we estimated area and volume of each tree to describe its crown shape. We calculated the crown area as the area of the vertical projection of the crown, approximated using the convex hull of the returns located within each segment, and the volume as the product of the area by the vegetation layer height (i.e. tallest height within the segment minus the two meter canopy threshold). Furthermore, we quantified the porosity of the crown through the fractional cover, as the proportion of canopy hits within the vegetation layer in relation to all hits within the segment (Riaño et al., 2004). We calculated minimum, maximum, mean, median, mode, standard deviation, variance, coefficient of variation, skewness, and kurtosis for height and intensity values of returns above two meters, to account for the canopy structure, based on the distribution, dispersion, and shape of the returns. Finally, to account for the variability of the point density within the study area, we calculated an accumulated intensity value normalized by density within the segment (García

et al., 2010) as follows:

$$cumCorr = \sum_{i=1}^n I_n \cdot \frac{\bar{d}_{flight}}{d_{tree}}$$

where $\sum_{i=1}^n I_n$ is the accumulated normalized intensities, $\bar{d}_{flight}$ is the mean point density for the whole dataset and d_{tree} is the point density of the tree, estimated as the number of returns by the area of the projected crown.

2.8 Tree classification and DBH estimation using Gaussian processes and ALS-derived metrics

A Gaussian process (GP) is defined as an infinite collection of random variables, any finite subset of which has a joint Gaussian distribution (Rasmussen and Williams, 2006). As mentioned in sect. 2.4, we applied a GP approach to solve two two-class classification problems, dead/live and conifer/hardwood, using the 25 ALS-derived metrics described in sect. 2.7 and to estimate DBH of dead conifer trees from two ALS metrics: height and crown area. To evaluate performance of our tree classification and DBH estimation methods we used a standard Leave-p-Out (LPO) cross-validation technique. We generated 100 random partitions of the data into training (70%) and test (30%) subsets and calculated the respective algorithm performance statistics for each partition. First, we discuss the DBH estimation by the Gaussian process regression that we find conceptually simpler than the GP-based classification approach discussed in sect. 2.8.2.

238 2.8.1 DBH estimation

In a generic form, the regression model for estimating tree DBH from a vector of ALS-derived metrics, e.g. height and crown area, can be written as

$$d = f(x) + \varepsilon,$$

239 where d is the DBH value for a tree with the ALS metrics in vector x , function f
 240 is an unknown underlying observation process model; and ε represents noise and/or
 241 unmodeled factors.

242 In the GP-based formulation of the regression problem, the DBH of an individual
 243 tree is considered a normally distributed random variable, and not a single unknown
 244 deterministic quantity, as e.g. in a classic regression analysis. We further assume that
 245 for any tree group, the joint probability distribution of their DBH is a multivariate
 246 normal distribution. Thus collectively, the actual DBH for all trees in the study site
 247 can be viewed as a finite sample from a Gaussian stochastic process f , with mean
 248 function $m(x)$ and a covariance function $K(x, x')$, commonly called a kernel.

249 If functions m and K were known, then for any test tree with input ALS metrics in
 250 vector x^* the true parameters of the normal distribution for the DBH d^* would also
 251 be known and could be used to predict the most likely DBH value and derive the pre-
 252 diction error estimates. In reality however, m and K are never known, and therefore
 253 need to be estimated based on the following three types of information:

- 254 1. available training samples for which both the feature vector x and the output

255 DBH value d are known;

256 2. assumptions about a parametric form of the covariance function K , which
257 controls for the GP model complexity; and

258 3. assumptions about the noise term ε .

Our training samples included of $N_{tr} = 396$ conifer snags located and measured during the field campaign, and described in sect. 2.3. Their DBH values range from 10 to 160 cm, with mean 45.2 cm and the std 24.6 cm. Furthermore, we chose the covariance function required by item 2) to be a squared exponential kernel $K(x, x')$:

$$K(x, x') = \sigma^2 \exp \left[-\frac{1}{2} \sum_{p=1}^P w_p (x_{ip} - x'_{ip})^2 \right],$$

259 with $(P + 1)$ free parameters: $\sigma, w_1, \dots, w_P$. Parameter σ is the unknown standard
260 deviation of a noise-free DBH signal that properly scales the covariances; σ_n is the
261 standard deviation of the noise; and $w_1, \dots, w_P$ are non-negative weights defining
262 the similarity measure in the P -dimensional metric space. When the input ALS met-
263 rics are similarly scaled, their weights also provide a relative measure of relevance for
264 modeling the output DBH. Our original ALS-derived metrics, however, had very dif-
265 ferent scales, and therefore were normalized into the range between 0 and 1. Finally,
266 the noise term was assumed to take the simplest form. Specifically, for each tree
267 and for each feature the noise was assumed to be independent and identically dis-
268 tributed according to a normal distribution $\mathcal{N}(0, \sigma_n)$, where σ_n is the noise standard
269 deviation, which is another free parameter to be estimated.

270 Our formulation of the GP model also implies that the differences between the ob-
 271 served values of DBH and the predicted values also follow the same GP model, albeit
 272 with the constant zero mean (Rasmussen and Williams, 2006). In other words, the
 273 mean value of the DBH for a new tree can be derived from the training tree DBH
 274 values, as soon as kernel K is found. Thus, our Gaussian process regression model
 275 is controlled by a vector of free hyperparameters $\theta = \{\sigma, \sigma_n, w_1, \dots, w_P\}$.

With all necessary pieces of information in place, θ and d^* can be found using the
 maximum-likelihood (ML) principle. Given the assumptions of our model, the log
 likelihood maximized with respect to θ is a Gaussian likelihood

$$\log p(d|X, \theta) = -\frac{1}{2}d^T K_d^{-1}d - \frac{1}{2}\log|K_d| - \frac{Ntr}{2}\log 2\pi,$$

276 where $K_d = K + \sigma_n^2 I$, and K is the matrix of training tree DBH covariances. The
 277 first term increases with a better fit to the available training tree data, whereas the
 278 second term penalizes our regression model for complexity. In this way, the ML
 279 estimation for the GP model also acts as a covariance model selection procedure
 280 aimed at minimizing the risk of overfitting the model. The Gaussian likelihood can
 281 have multiple local maxima, and therefore the ML estimation requires setting initial
 282 values for the hyperparameters. In our experiment, the following initial values were
 283 used: $\sigma = 1$; $\sigma_n = 0.1$, and $w_p = 1$.

284 Using the obtained ML estimate of θ , the DBH values were found $(K_* [K + \sigma_n^2 I]^{-1} d)$,
 285 which is the mean value of the DBH posterior distribution (see Gibbs (1998) for
 286 further details).

287 2.8.2 Tree classification

288 When a Gaussian process approach is applied to a two-class classification problem,
289 the target random variable is a discrete class label $y = \{0, 1\}$. Given a vector of ALS
290 metrics x , the class label assignment by GP classification requires modeling the tree
291 posterior probability for one of the classes, which we denote by $p(x)$.

292 For each classification problem, we selected ALS metrics that maximize inter-class
293 and minimize within-class differences in the training data. For the snag/alive clas-
294 sification problem, these metrics included 12 ALS metrics: five structural metrics
295 (minimum height, height coefficient of variation, fractional cover, volume, and area)
296 and seven intensity metrics (maximum, minimum, median, variance, coefficient of
297 variation, and accumulated corrected intensity). For hardwood/conifer classifica-
298 tion, we used nine metrics, including seven structural metrics (maximum, median,
299 standard deviation, and skewness of heights; fractional cover, volume, area) and
300 two intensity metrics (minimum intensity and accumulated intensity normalized by
301 area). As in the case of regression (sect. 2.8.1), all ALS-metrics were normalized
302 to fit the interval between 0 and 1. Our training sample for snag/live classification
303 included 497 trees measured in the field (sect. 2.3), and for conifer vs. hardwood
304 snag problem 343 training trees were used.

305 Conceptually, the posterior probability estimation proceeds in two steps (Rasmussen
306 and Williams, 2006). First, a GP regression approach with the squared exponential
307 kernel for the covariance function (as in sect. 2.8.1) is used to map the ALS feature
308 vector x into an intermediate one-dimensional latent random variable $z = f(x)$. This

latent variable, in effect, models relative likelihood of class membership as a stochastic function f of the feature vector x . The second step is to apply a deterministic sigmoid function transforming z from its native domain into the range between 0 and 1, so that it can be viewed as the class probability. In this work we used the Gaussian cumulative distribution function, $\Phi(z)$, also called the error function.

The parameters of the GP model for classification include σ , and $w_1, \dots, w_P$, where P is the number of ALS metrics. In each classification problem, the maximum-likelihood estimation of the parameters was performed via the Expectation Propagation (EP) algorithm (Minka, 2001; Rasmussen and Williams, 2006), with σ and all weight w_p initialized to 1.

2.9 Black-backed Woodpecker habitat mapping

Based on conifer snag basal area across Black-backed Woodpecker home ranges studied by Tingley et al. (2014), we mapped contiguous areas with potential (i.e., snag basal area $>$ the lowest mean basal area observed across any Black-backed Woodpecker home range) or optimal (i.e., snag basal area $>$ the 50th percentile of average basal area values observed across any Black-backed Woodpecker home range) Black-backed Woodpecker habitat. To estimate the accuracy of the resulting overall basal area mapping, we compared the measured and mapped conifer snag basal area over the field plots. Finally, we estimated the total potential and optimal habitat area and assessed its degree of fragmentation.

330 **3 Results**

331 **3.1 Tree detection**

332 Our results show that the percentage of detected trees varies with its stem diameter
333 (Table 2). The algorithm detected 99% of trees with large stem diameter with only
334 commission errors and 75% of trees with medium stem diameters (Table 2). Note
335 that 25% of medium size trees remained undetected, because they were suppressed
336 by larger trees. The algorithm detected 87 % of trees with stem diameter larger than
337 30 cm. The inability to detect suppressed trees is a well-known drawback of CHM-
338 based tree delineation algorithms. Although the small trees objectively represent the
339 greatest challenge, we have been able to map nearly 40% of them.

340 **3.2 Classification and stem diameter estimation results**

341 **3.2.1 Snag/live classification**

342 The results presented in Table 3 demonstrate high accuracy of snag/live classification,
343 with the overall correct classification rate of 91.8% and a kappa coefficient of 0.84.
344 Both, commission and omission errors are under $10\% \pm 3\%$, based on the LPO
345 cross-validation (Table 3).

346 The model relies on the coefficient of variance (CV) as the only metric related with
347 heights. Intensity data is used in the model through the maximum, variance, co-
348 efficient of variation, with CV as the most relevant one for the model. Finally,

the model uses shape related metrics, mostly area but also volume to discriminate between classes (Figure 3).

Figure 4 shows how the snags distribution aligns with the burned area in Figure 2, where moderate and high severity sites correspond to partial and complete tree mortality, respectively. Figure 4 also shows how live trees abound at higher elevations.

3.2.2 Conifer/Hardwood classification

Similar to snag/live classification, the Gaussian process technique effectively discriminates between snag hardwood and conifer trees. Table 4 shows, based on the LPO cross-validation, that the correct classification rates for both classes are very similar and approach 85%, with std of 5%. The kappa coefficient for the snag type classification is 0.64. Both, commission and omission errors are under $16\% \pm 5\%$.

Both maximum and median heights have a relevant role in the classification since conifer snags tend to stand taller. The minimum value of intensity clearly has an impact on the classifier. In terms of metrics related to height, the standard deviation, skewness, and fractional cover are also relevant for the model. The analysis shows that conifer snags can reach larger values of standard deviation and fractional cover than dead hardwoods. Finally, the model also uses the area metric to separate between classes (Figure 3).

Snag maps by forest type (Figure 4) show that hardwoods are somewhat distributed across the study site, whereas conifers exhibit more apparent spatial clustering,

370 mainly south-east and central areas of Stanislaus National Forest and much of the
371 burned portion of Yosemite National Park.

372 **3.2.3 DBH estimation results**

373 Our results show that the Gaussian process regression provides an effective method
374 to estimate stem DBH from maximum height and area, with the determination
375 coefficient $R^2 = 0.81$ and $\text{rmse} = 10.6$ cm. The model performs similarly for medium
376 and large stem trees, as seen from the scatter plot of true versus GPR-predicted stem
377 diameter for 119 snag conifer trees in Figure 5. Table 5 provides more information
378 about estimation accuracy per tree size class. For small trees, the absolute errors are
379 smaller, however the relative rms error (Table 5) is larger than for the other two size
380 classes. The use of relative error is more appropriate to understand the performance
381 of the model per tree size class, particularly for medium and large trees, since it is not
382 affected by the size of the stem itself. Medium and large trees are more important
383 for Black-backed Woodpecker foraging habitat than small trees, and therefore, better
384 accuracy of our model for medium and large trees is an advantage. Stem diameters
385 for small trees tend to get underestimated with the GP modeling, while no significant
386 bias is observed for medium trees (Figure 5).

387 The GP-based estimation results provide a significant improvement over the tradi-
388 tional DBH modeling approach based on allometric equations (Keyser and Dixon,
389 2008). The allometric model has a lower R^2 value (0.73) and larger scatter, as shown
390 in Figure 5. Furthermore, the errors of the GP estimation are reduced by almost a

half, with respect to the allometric approach ($\text{rmse} = 16.5 \text{ cm}$ and relative error = 43.5 %), thus providing a more accurate input into deriving basal area calculation. Conifer snags basal area-weighted mean tree diameter map (Figure 4) showed how large DBH trees dominate at the highest elevations within Yosemite National Park and the north-west area of the Rim Fire within Stanislaus National Forest.

3.3 Black-backed Woodpecker habitat mapping results

Optimal and potential habitat for Black-backed Woodpecker comprise 53.7 km^2 and 58.4 km^2 , respectively, representing 5.1 and 5.6% of the overall footprint of the Rim Fire. In many instances, optimal habitat areas are adjacent to or surrounded by areas mapped as potential habitat, resulting in relatively large patches of apparent habitat. Some of the larger habitat patches are localized near the center of the burned area on Stanislaus National Forest, and to the east, near the border with Yosemite National Park. These large fragments comprise approximately 1 km^2 each, whereas most of the other optimal habitat areas, particular in Yosemite National Park, are more highly fragmented. Comparing the measured and mapped conifer snag basal area over the field plots showed that our method mapped $81.3\% \pm 18.7\%$ of the total basal area (Figure 6). Our estimates of the extent of potential and optimal Black-backed Woodpecker habitat in the Rim Fire should therefore be considered lower bounds.

410 4 Discussion

411 Large stem diameter trees are detected at markedly higher rates than those with
412 small diameter stems, likely because small trees are commonly suppressed by larger
413 overstory trees and thus are mostly undetectable by LiDAR. This result is in agree-
414 ment with previous studies (Solberg et al., 2006; Chen et al., 2006; Reitberger et al.,
415 2009; Duncanson et al., 2014). Although under-detection of small trees leads to
416 underestimation of basal area, we believe the impact of this error on Black-backed
417 Woodpecker habitat mapping evaluation is minimal, due to the species preference
418 for medium and large snags for foraging. Additionally, the contribution of large and
419 medium stems to the basal area estimation in our field plots is 36 % and 48 % re-
420 spectively, what reinforces the small impact of undetected small trees in our work.
421 Nevertheless, if our method is also to be applied for wildlife species that utilize smaller
422 diameter snags, it should include additional steps to refine the Watershed Segmen-
423 tation algorithm output. Examples of successful such post-segmentation refinement
424 steps can be found in Reitberger et al. (2009) and Duncanson et al. (2014).

425 A common factor determining the accuracy of all tree detection approaches is the
426 ALS data point density. Our method used a high-density ALS dataset, averaging 19
427 points per m^2 . While a lower density data would negatively impact detection rates
428 for both live and snag trees, the impact on snags would be more dramatic, because
429 small objects like snags may no longer have a minimal number of returns to form a
430 separate segment. Indeed, even with our high-density data, our snags often provide
431 just a few above-ground returns, with fewer hits when defoliated (e.g. < 10). The

432 mean number of canopy ALS points per segment was 454 ± 552 . We expect that
433 lower density might also have a negative impact on the classifications, and DBH
434 estimation.

435 The main advantages of using Gaussian processes include the probabilistic, inter-
436 pretable outputs and uncertainty information, and a built-in mechanism for auto-
437 matic selection of relevant metrics based on the covariance kernel weights. Not sur-
438 prisingly, our results suggest that the chosen ALS metrics related to return intensity
439 are highly informative for snag identification (see Figure 3, top graph). These met-
440 rics include maximum (Max-I), coefficient of variation (CV-I), and variance (Var-I).
441 Indeed, metrics CV-I and Var-I are meaningful as they tend to have lower values
442 for live trees than for snags; whereas maximum intensity is expected to be lower for
443 snags. This high contribution of intensity-related metrics is in agreement with other
444 studies (Kim et al., 2009; Korpela et al., 2010) that relate lower intensity with snags,
445 for which returns are based on reflections from burned stem and branches. However,
446 it contradicts the work of Yao et al. (2012), who found intensity metrics only moder-
447 ately important to detect 71 % of snags under leaf-off conditions. The importance of
448 the canopy penetration metric in the model of Yao et al. (2012) is consistent with the
449 relevance of fractional cover in our results. It should be noted that fractional cover
450 is not always enough to differentiate snags from live trees. Similar fractional cover
451 values can correspond to snag and live conifer because conifer snags often retain
452 dead needles. However, in cases in which the snags have completely lost their foliage
453 they effectively relate to low fractional cover values. Consistent with our results,
454 the variability of heights have been found useful to identify snags using area-based

455 approaches (Martinuzzi et al., 2009; Bater et al., 2009). For example, Martinuzzi
456 et al. (2009) presents detection rates of 86% to 88% for different diameter classes
457 using height and topography-related metrics with a plot-based approach, but only
458 when additional forest successional data are used. Our snag detection rate is also
459 higher than that of Wing et al. (2015), who present an overall detection of 56 % for
460 stem diameters larger than 25 cm.

461 Separation of conifer and hardwood snags, relied primarily on height-related metrics,
462 mainly the median but also the maximum and standard deviation. The importance
463 of both maxima and median heights are explained from the fact that conifer snags
464 tend to stand taller. The area occupied by the snag and its fractional cover are also
465 relevant for the model (Figure 3). The data show that conifer snags on average
466 have larger values of standard deviation of height and fractional cover than dead
467 hardwoods, with values in common for both classes. This might be due to the fact
468 that conifer snags might retain brown needles and therefore have large fractional
469 cover and standard deviation, whereas dead hardwood have lost their foliage and
470 have lower values in both metrics.

471 The arrangement of the canopy, depending on forest type, has been successfully
472 related to intensity (Kim et al., 2009; Ørka et al., 2010). Some studies found the
473 average of intensities to be less for conifers than for hardwoods (García et al., 2010;
474 Vauhkonen et al., 2014). In our study both forest types are dead and unsurprisingly
475 intensity plays a minor role in the classifier. However, we note that lower values of the
476 minimum intensity characterize conifer snags which is in agreement with Vauhkonen
477 et al. (2014) and García et al. (2010). Our classifier has an overall accuracy of

478 84.8 %. This result is comparable with studies that classify live conifers from leaf-
479 off hardwoods such as Kim et al. (2009) who achieved a classification accuracy of
480 83.4%. It must be noted that some snags in our samples were pole-shaped (3.7% of
481 our measured trees), which are difficult or impossible to differentiate.

482 Our estimation of stem diameters for conifer snags using Gaussian process regression
483 proved reliable and comparable with other studies in terms of the correlation coef-
484 ficient (Popescu, 2007; Yao et al., 2012); however, the rmse is larger than expected
485 (Table 5). Popescu (2007) for example, estimated stem diameter with a rmse of 4.9
486 cm while Muss et al. (2011) even though estimating DBH with lower coefficient of
487 correlation than our results, had lower rmse. It must be noted that in those studies
488 trees are alive, whereas in our case broken or partially consumed snags introduced
489 noise into the model. Furthermore, our field data had similar stem diameters for
490 very different tree heights. In general, the method overestimates very large stem
491 diameters (> 90 cm) while large and medium diameter trees are estimated with no
492 significant bias (Figure 5 and Table 5). Nevertheless, our Gaussian process-based
493 method provides a significant improvement over the traditional use of site-specific
494 conifer allometric equations (Figure 5). The presented method for mapping conifer
495 snag basal area represents a chain of steps, each of which factoring in the accuracy of
496 the final map and any derived metrics of habitat mapping, such as the ones discussed
497 in sect 3.3. Furthermore, the combined effect of tree delineation error, confusion in
498 snag/live and conifer/hardwood classifications, and the DBH modeling residuals on
499 the final product, is also expected to vary with the forest density and gap structure,
500 species composition, and other factors.

501 Although ALS accommodates the extraction of relevant 3D structural metrics at
502 different level of details, its potential in wildlife studies is not being fully exploited
503 if detailed habitat attributes are not derived at grain sizes known to be relevant to
504 conservation and management (Müller and Brandl, 2009). One of the main advan-
505 tages of the presented methodology is the use of a single-tree approach that enabled
506 the aggregation of estimated basal area at the scale required by the habitat model
507 without loss of information. This would not be the case for area-based estimations
508 that, if rescaled, will introduce an unknown impact into habitat modelling results
509 (Garabedian et al., 2014). In addition, home ranges are not homogeneous (Tingley
510 et al., 2014) and a single tree approach provides the flexibility of aggregated results
511 in different spatially discriminant shapes.

512 Credible assessments of habitat for indicator species or species of management con-
513 cern can help land managers make difficult decisions about which burned stands to
514 harvest or which to retain for wildlife habitat. This model-based approach is partic-
515 ularly useful for Black-backed Woodpecker, which may not fully colonize new burned
516 areas until many months (or even multiple years) after the fire. On-the-ground occu-
517 pancy surveys conducted on this timeline may be too late to inform decisions about
518 post-fire forest management. In contrast, when suitable ALS data is available, pre-
519 dicted habitat can be mapped rapidly, as required by land managers who need to
520 act while fire-killed trees are still merchantable.

521 The methodology presented provides an effective way to detect and identify snags at
522 the single-tree level and characterize their type and size with uncertainty estimations
523 using only high-density ALS data. Furthermore, it provides wall-to-wall coverage of

524 predicted habitat for the Black-backed Woodpecker across the full extent of a recent
525 megafire. Black-backed Woodpeckers are strongly associated with habitat conditions
526 created by mid- and high-severity fires. Our habitat map provides a tool that land
527 managers can use for identifying forest stands that, if left unharvested, are likely
528 to be of greatest value to Black-backed Woodpeckers. We caution, however, that
529 managing habitat for one wildlife species that is strongly associated with recently
530 burned forest (or any other habitat) does not necessarily ensure that the needs of all
531 such species will be met (Landres et al., 1988).

532 The maps generated can be used as a base layer to improve habitat modeling at broad
533 scales (Tingley et al., 2014) as well as an exploratory tool to study structural patterns
534 in combination with occupancy or biodiversity data (Vierling et al., 2008). Overall,
535 the methodology presented can be used in a variety of applications related to biodi-
536 versity, environmental health and vegetation dynamics studies, such as quantifying
537 tree mortality attributed to increases in temperature and drought or forests affected
538 by insect infestation. In postfire scenarios, a snag map can be used to improve burn
539 severity estimation (Gajardo et al., 2014), precise location of green islands for re-
540 seeding, and as a baseline for future assessment of vegetation regeneration after fire
541 (Abella and Fornwalt, 2014). Finally, the classification of snags by its forest type and
542 its diameter size estimation can be applied in dead biomass retrieval studies (Kim
543 et al., 2009). Dead biomass estimation is compelling in a climate change context,
544 given the critical role burned trees play in carbon sequestration, retaining carbon for
545 decades, and releasing it gradually by decomposition (Siccama et al., 2007).

546 **5 Conclusion**

547 Our study shows the utility of high-density discrete ALS data for mapping the mor-
548 tality status, type, and stem diameter of trees in a recently burned forest. These
549 maps, in conjunction with habitat models based on snag abundance and character-
550 istics, allow identification of habitat for Black-backed Woodpecker and other wildlife
551 species. This work contributed to developing a fast and efficient operational method-
552 ology to characterize the extent of burned forest at the tree level, which can greatly
553 aid wildlife habitat assessment, forest management, and conservation planning after
554 megafires. Timely, spatially distributed characterization of burned forest will become
555 increasingly important in light of projected increase in megafire frequency. A poten-
556 tial avenue for future development would involve the identification of hotspots for
557 multiple snag-dependent taxa within the same burned landscape, allowing an inte-
558 grated, multi-species approach to forest management and species conservation.

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TABLES

Table 1: ALS metrics used in the classifications and regression.

Metric name	Metrics description
max h	Maximum height
min h	Minimum height
mean h	Mean height
med h	Median height
mode h	Modal height
std h	Standard deviation of heights
var h	Variance of heights
cv h	Coefficient of variation of heights
skew h	Skewness of heights
kurt h	Kurtosis of heights
fC	Fractional cover
Vol	Volume
max i	Maximum intensity
min i	Minimum intensity
mean i	Mean intensity
med i	Median intensity
mode i	Modal intensity
std i	Standard deviation of intensities
var i	Variance of intensities
cv i	Coefficient of variation of intensities
skew i	Skewness of intensities
kurt i	Kurtosis of intensities
area	Area
cum i	Accumulated intensity
cumCorr i	Corrected accumulated intensity

Table 2: Individual tree detection accuracies for three DBH classes: small(10 to 30 cm), medium (30 to 60 cm), and large (greater than 60 cm).

	All	Small	Medium	Large
Commission.E.,%	12.3	10.4	8	17
Omission.E.,%	45.7	61.2	25	1

Table 3: Confusion matrix for the snag/live classification. Values shown are the mean $\pm$ std cross-validated results with 100 replications.

		Reference		Total
		Snag	Live	
GP	Snag	96.9 $\pm$ 6.8	7.3 $\pm$ 3.0	104.2
	Live	10.1 $\pm$ 3.1	98.7 $\pm$ 6.7	108.8
	Total	107	106	213
	Producer's accuracy, %	90.51 $\pm$ 2.8	93.1 $\pm$ 2.8	
	User's accuracy, %	93.04 $\pm$ 2.7	90.72 $\pm$ 2.7	

Table 4: Confusion matrix for the conifers/hardwood classification. Values shown are the mean $\pm$ std cross-validated results with 100 replications.

		Reference		Total
		Conifer	Hardwoods	
GP	Conifers	62 $\pm$ 5.6	11.5 $\pm$ 4	73.5
	Hardwoods	11.4 $\pm$ 3.7	62.2 $\pm$ 5.1	73.6
	Total	73.4	73.7	147
	Producer's accuracy, %	84.5 $\pm$ 5.0	84.7 $\pm$ 5.1	
	User's accuracy, %	84.5 $\pm$ 5.0	84.5 $\pm$ 4.5	

Table 5: DBH estimation performance statistics, including mean error (ME), root mean-squared error (RMSE), mean absolute error (MEA) and relative error (RE) normalized by mean DHB. Error values shown are the mean $\pm$ std over 100 replications.

GP regression	ME (cm)	RMSE (cm)	MAE (cm)	RE (%)
Small	3.3 $\pm$ 1.2	7.2 $\pm$ 1.4	5.2 $\pm$ 0.8	20.3 $\pm$ 2.1
Medium	1.2 $\pm$ 1.4	8.7 $\pm$ 1	6.8 $\pm$ 0.8	16 $\pm$ 1.9
Large 3	-5.4 $\pm$ 2.6	14.6 $\pm$ 2.1	11.2 $\pm$ 1.5	18.6 $\pm$ 3.6
All	0.01 $\pm$ 1.2	10.6 $\pm$ 1	7.6 $\pm$ 0.6	18.1 $\pm$ 1.3
$R^2 = 0.81$				

FIGURES

Figure 1: Workflow diagram for habitat mapping described in Sect. 2.

Figure 2: Location and Landsat-based burn severity (% change in canopy cover) of the 2013 Rim Fire on Stanislaus National Forest and Yosemite National Park (Miller and Thode, 2007)

Figure 3: Relevance of the metrics in the GP snag/live (top) conifer/hardwood (bottom) model obtained from the non-negative weights (w_P) of the kernel.

Figure 4: Number of live trees per pixel (A), number of hardwood snags (B), number of conifer snags (C), and conifer snag basal area-weighted mean tree diameter, m (D). Pixel resolution = 50 m.

Figure 5: Scatterplot of observed and predicted conifer snag DBH using Gaussian process regression (top) and site-specific allometric equations for conifers (bottom). Solid lines show the least-squares linear relationship between the observed and predicted DBH. The 1:1 relationship is represented by a dashed line.

Figure 6: Habitat map for the Black-backed Woodpecker across the Rim Fire, based on pre-harvest conditions and conifer snag basal areas (csBA) thresholds obtained from Tingley et al. (2014). Pixel resolution = 20 m.