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Mortality predictions of fire-injured large Douglas-fir and ponderosa pine in Oregon and Washington, USA

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ABSTRACT

Wild and prescribed fire-induced injury to forest trees can produce immediate or delayed tree mortality but fire-injured trees can also survive. Land managers use logistic regression models that incorporate tree-injury variables to discriminate between fatally injured trees and those that will survive. We used data from 4024 ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.) and 3804 Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) trees from 23 fires across Oregon and Washington to assess the discriminatory ability of 21 existing logistic regression models and a polychotomous key (Scott guidelines). We used insights from the validation exercise to build new models for each tree species and to identify fire-injury variables which consistently produce accurate mortality predictions. Only 8% of Ponderosa pine and 14% of Douglas-fir died within 3 years after fire. The amount of crown volume consumed, the number of bole quadrants with dead cambium and the presence of beetles were variables that classified most accurately, but surviving trees in our sample displayed a wide range of fire injury making the accurate classification of dead trees difficult. For ponderosa pine, our new model correctly classified 99% of live trees and 12% of dead trees while the Malheur model (Thies et al., 2006) correctly classified 95% of live trees and 24% of dead trees. The Scott guidelines accurately predicted at least 98% of live ponderosa pine trees but less than 2% of dead ponderosa pine. For Douglas-fir the Scott guidelines accurately predicted at least 80% of live trees and generally less than 10% of dead trees. Misclassification rates can be controlled by the choice of decision criteria used in the models and managers are encouraged to consider costs of the two types of misclassifications when choosing decision criteria for specific land management decisions.

1. Introduction

The frequency and severity of wildfire in western landscapes is of critical concern and management of the post-fire landscape will be especially challenging. Many forested ecosystems rely on naturally occurring fire, but fire suppression over the past 100 years led to the accumulation of large fuel loads in some systems which potentially increase wildfire severity (Schoennagel et al., 2004; Peterson et al., 2005). There is concern that future warmer climates may increase the frequency and the severity of forest fires and change wildfire patterns and will have far reaching effects on human populations (e.g., Chapin et al., 2008). Land managers and policy makers face difficult decisions about the use of limited resources and land management strategies in the face of forest fires (Stephens et al., 2013). The post-fire landscape typically includes a range of fire severity patches with many still-living trees that have been injured by the fire. The fate of these still-living trees that may die will influence decisions regarding timber salvage, future tree stocking of fire disturbed landscapes, and wildlife conservation. Therefore, predictions of post-fire tree mortality for a variety tree species and forest types will continue to be important foundational information for forest managers.

Injury to trees from wildfire and prescribed fire can produce mortality that is not immediately apparent and environmental stress before and after a fire may also contribute to tree mortality in years after a fire (Hood and Bentz, 2007). Dozens of statistical logistic regression models have been developed to predict post-fire tree mortality from fire injury variables before tree mortality is clearly apparent, (see Woolley et al., 2012 for a review) and some are incorporated within larger fire behavior and effects computer models used to support land management decisions (Reinhardt et al., 1997; Hood et al., 2007b; Lutes, 2016).

A polychotomous field key, known as the Scott guidelines, was developed (Scott et al., 2002) and refined (Scott and Schmitt, 2006)

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to predict conifer mortality in northeastern Oregon. Trees receive a numerical score based on pre-fire site condition and fire-injury variables and a low, moderate or high probability of survival based on the score. Different DBH (diameter at breast height) classes of different tree species are scored differently. This method has been used to classify tree survival on 24 fires to date (Don Scott, pers. comm.).

Published logistic regression models have been tested on independent data. The modification of the Ryan and Amman model used in FOEFM (Lutes, 2016) was tested for 13 coniferous species from 21 fires across the western US (Hood et al., 2007b). The Ryan and Reinhardt model (Ryan and Reinhardt, 1988) was tested using ponderosa pine (*Pinus ponderosa* Dougl. ex Laws) in 3 wildfires in Montana (Finney, 1999). A model that included the presence of Douglas-fir beetles was tested on Douglas-fir (*Pseudotsuga menziesii* (Mirbel) Franco) in 3 wildfires in Montana and Wyoming (Hood and Bentz, 2007). The Stephens and Finney model (Stephens and Finney, 2002) was developed for ponderosa pine in one prescription fire in California and later tested on the same tree species for 2 wildfires (Hood et al., 2010). Sieg et al. (2006) developed a model for ponderosa pine from fires that burned in 2000 in Arizona, Colorado, South Dakota and Montana and validated the results on a 2001 fire from South Dakota. The Malheur model for ponderosa pine in eastern Oregon was validated on 10 prescribed and 7 wildfires in Oregon and Washington (Thies and Westlind, 2012).

Recently, post-fire mortality and fire injury variables were collected for 23 wildfires across Oregon and Washington, providing an opportunity to test published models for Douglas-fir and ponderosa pine in this region. Our objectives are to (1) assess the ability of previously published logistic regression models to predict 3-year post-fire mortality in Oregon and northern Washington state, including the Malheur model and the Scott guidelines, (2) to identify a new model and suites of fire-injury variables that accurately discriminate between live and dead trees in that region and (3) suggest a management approach to post-fire tree mortality modeling in Oregon and Washington.

2. Statistical context and methods

2.1. Field sampling

Twenty-three wild and prescribed fires that occurred between 1999 and 2007 from southwest Oregon to northeastern Washington were identified by local USDA Forest Service Forest Health Protection offices in cooperation with USDA Forest Service National Forest and District offices (Appendix A, Fig. 1). Fires were selected when the burned perimeter included areas of mixed fire severity with apparently fire-injured, but not dead, trees and no post-burn management activities were planned for those areas.

Field crews were requested to sample at least 500 trees from each fire if possible, from stands that were accessible from nearby roads. Crews were instructed to choose the larger trees in the stand for measurement if green needles and fire-injury were present. Sampling transects began with a haphazardly selected initial tree that met the selection criteria near the access road and subsequent haphazardly selected trees that met the selection criteria were sampled in a direction approximately perpendicular to the road into the burned forest. Each tree was tagged and the azimuth and distance to the next sampled tree was recorded for future relocation. The length of transects was limited by the time it would take to return to the road, typically about 20 min and the number of transects and the number of trees sampled in each fire was limited by the area available to collect data.

2.2. Field measurements and methods

Initial assessments of tree condition and fire-injury variables were completed during the summer of the year of the fire if the burn occurred early-to-mid summer. If the fire occurred in late summer or early fall, initial assessments and data collection occurred in the following spring after bud-break, or during the following summer. For fires in ponderosa pine evaluated in the year of the fire (usually prescribed burns), crown scorch was evaluated the year of the burn and crown volume killed confirmed the following season. Variables were chosen to match, or calculate, variables collected in previous studies of post-fire mortality.

The following data were collected in the initial field assessment for each tree.

- Tree species.
- Diameter at breast height (DBH) was measured to the nearest 0.25 cm on the uphill side of the tree at 1.37 m above mineral soil.
- Dwarf mistletoe rating was recording using the 6-class dwarf mistletoe rating system (Hawksworth, 1977).
- Percent of pre-fire crown volume that was killed relative to the space occupied by the pre-fire crown volume to the nearest 5% (Ryan, 1982).
- The distance from the ground to the following points on the tree, were recorded using an Impulse 200 Laser hypsometer (Laser Technologies, Englewood, CO). Measurements were taken on the uphill side of the tree perpendicular to the slope at a distance sufficient to obtain an accurate value.
  - Top of tree – Tree height (m).
  - Base of pre-fire tree crown (m).
  - Base of post-fire tree crown (m).
  - Upper limit of post-fire bole-blackening (scorch) – (m).

The following measurements were also made on four quadrants of each tree, numbered in clockwise order beginning with the downhill quadrant or with the south-facing quadrant on flat ground.

- Cambium, close to the ground-line, was assessed as dead or alive in each bole quadrant following Hood et al. (2007a). If necessary, bark was removed to within 0.25–0.50 of the cambium and a bark punch was drilled into the cambium.
- Bole scorch was scored as 0, 1, 2, or 3 in each quadrant of the tree bole following Ryan (1982).

After the initial assessment, every year, for up to five years, each tree was visually evaluated for mortality and evidence of bark beetle or wood borer infestation. Trees were recorded as dead in each year if no green foliage was visible or if the tree had fallen or broken off since the previous year. For ponderosa pine, the presence of red turpentine beetle (*Dendroctonus valens* LeConte) pitch tubes on the bole was recorded as well as infestation by western pine beetle (*Dendroctonus brevicomis* LeConte), mountain pine beetle (*Dendroctonus ponderosae* Hopkins). Ips spp. were determined by reddish boring dust on surface and bark crevasses. Douglas-fir beetle (*Dendroctonus pseudotsugae* Hopkins) infestation was determined by evidence of reddish-brown boring dust found in bark crevices on the lower portion of the tree's bole or on the ground at its base or presence of clear resin which has exuded from the upper level of attacks-typically 30–35 feet off the ground. No bark was removed from living trees to determine the success of the beetle infestation to avoid injury that may be detrimental to its survival. If the tree subsequently died, bark beetle galleries were examined to determine the species present.

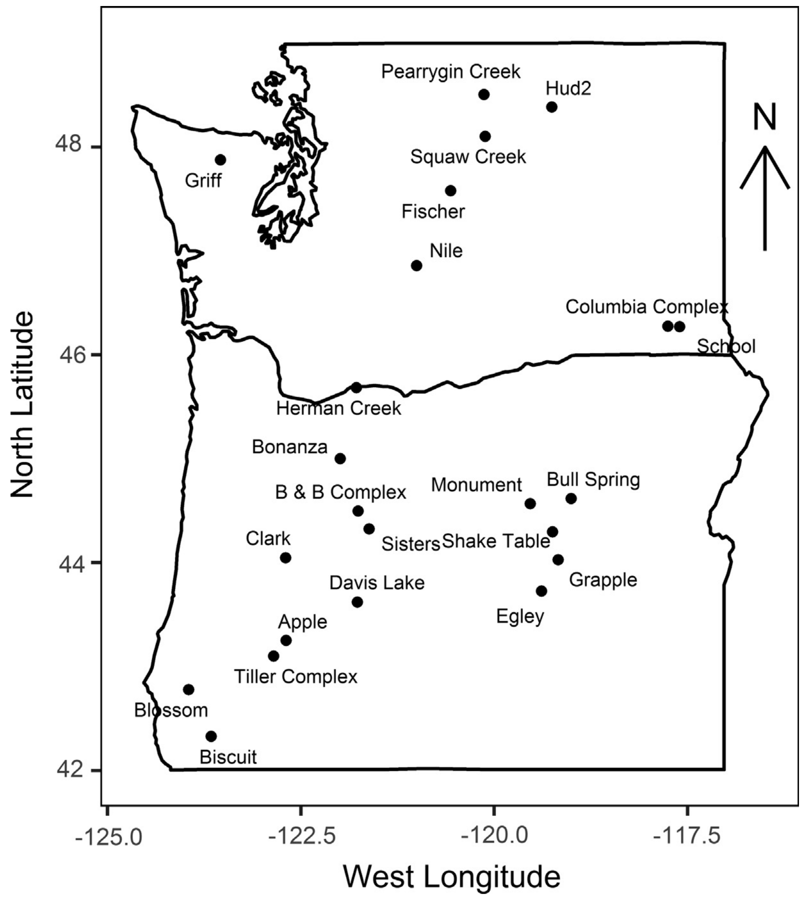

Fig. 1. Location of fires from which data were collected.

2.3. Data analysis

2.3.1. Summary of field data by fire type and region

We omitted trees from the analysis if they were initially recorded as dead or if any field measurements were missing. We omitted all trees of a species from subsequent analysis if a fire did not contain at least 50 trees of that species. Therefore, ponderosa pine from Biscuit, Shake Table or Tiller Complex fires and Douglas-fir from Grapple, Hud2, Monument, Pearrygin or Sharps Ridge fires were not included. The final dataset consisted of 3804 Douglas-fir and 4024 ponderosa pine trees.

For each tree species we graphed the proportion of dead trees over time for each fire. We found substantial increases (more than 14 percentage points) in the proportion of dead trees for each year until the 3rd year post-fire in all fires but increases of less than 3% after year 3 for each species. The sample size also decreased in the fourth and fifth year after fire because not all fires were visited for 5 years. For these reasons and because many previous models were based on third year mortality, we used 3-year mortality for further analysis.

We grouped all but one fire into three broad geographic regions based on average annual rainfall (PRISM Climate Group, Oregon State University, http://prism.oregonstate.edu, created (2010), vegetation zone (Franklin and Dryness, 1973). The Apple, Biscuit, Blossom, Bonanza, Davis Lake, Hermann Creek and Tiller Complex fires were labeled as fires from southwest Oregon (SW.OR). The Fischer, Hud2, Nile, Pearrygin and Squaw Creek fires were labeled as northern Washington fires (N.WA). The B and B, Bull Springs, Columbia Complex, Egley, Grapple, Monument, School, Shake Table, Sharps Ridge and Sisters fires were labeled as the eastern Oregon group (E.OR). The Griff fire burned in the Olympic Peninsula and was summarized separately.

For each combination of region and fire type (wildfire or prescribed), we combined all trees of each species from all the fires in the region. Ponderosa pine was present in wild and prescribed fires in northern Washington and in eastern Oregon. Douglas-fir was present in wild and prescribed fires in northern Washington and in wildfires in eastern and southwest Oregon. We graphically summarized the distributions of the primary field measurements bulleted below, by fire type and region, and for live and dead trees to determine if analyses should be conducted separately by fire type or region (Ganio et al., 2015). Graphical summaries are presented in Appendix A.

- Tree DBH in centimeters (DBH).
- The percent of crown volume scorched (CVSPERC).
- The maximum height of fire scorch (area blackened by fire) on the tree bole in meters (BSHM).
- The percentage of the bole that was charred (CHAR).
- The bole scorch rating in each of 4 quadrants around the tree. Rating was 0 for unburned, 1 for lightly charred, 2 for moderately charred and 3 for deeply charred. The number of dead cambium samples ranging from 0 to 4 (CKR).
- The presence (or absence) of Douglas-fir beetle (DFBAR3) on Douglas-fir during the first through third year post-fire.
- The presence or absence of western pine beetle, mountain pine beetle, red turpentine beetle or Ips sp. during the first through third year post-fire (BEETLE3) on ponderosa pine.

2.3.2. Validation of previously published logistic regression models

To address whether existing post-fire mortality models could be used effectively in the regions covered by our fires, we applied 21 previously published models to our data (described in Appendix B). For ponderosa pine we tested 5 prescription fire models, 6 wildfire models and 3 models built from trees injured in both wild and prescription fires. For Douglas-fir, we tested 2 wildfire models, 3 prescription fire models and 3 models created from trees injured in both wild and prescription fires. Because our estimates of crown scorch are assumed to represent both scorch and crown kill we only used models that did not distinguish between them.

We calculated the following fire-injury variables from our field measurements to use as explanatory variables in the previously published regression models.

- Pre-fire Crown height = (tree height) – (distance to the base of pre-fire crown).
- Post-fire Crown height = (tree height) – (distance to the base of post-fire tree crown).
- CKR: Cambium Kill Rating = total # of dead cambium samples (0–4).
- Average Ground Char = Average of the 4 ground char ratings on each tree when it was present.
- Crown length killed – (Pre-fire crown height) – (post-fire crown height).
- Bole Scorch Rating = Average of the 4 bole scorch ratings for quadrants with bole scorch present.
- RTB1 – The presence or absence (1/0) of red turpentine beetle one year after fire.

We applied each published model to observations from the same tree species and type of fire that were used to build the original model. We combined data from wild and prescribed fire for each species and applied each model to this larger set of trees. We summarized the average discriminatory ability for each model with the area under the receiver operating characteristic curve (AUC) where values closer to 1 indicate better discriminatory ability (Saveland and Neuenschwander, 1990) and its 95% confidence interval (Table 1).

Logistic regression models can be reported in different forms which affect whether or not coefficients are reported as positive or negative values. In this study, we always report values of coefficients corresponding to this form of the logistic regression:

$$P_m = 1/[1 + \exp(-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p))]$$

where P_m is the probability of mortality and $X_1, X_2, \ldots, X_p$ are the discriminatory variables in the model.

2.3.3. Validating the Scott guidelines

We automated the Scott guidelines using Mathematica (Wolfram Research, 2016). Trees were classified separately based on DBH and tree age as described by the guidelines. Ponderosa pine $\geqslant$53.34 cm and Douglas-fir $\geqslant$50.80 cm; and $\geqslant$180 years old were evaluated with different criteria than smaller and younger trees (Scott et al., 2002; Scott and Schmitt, 2006).

2.3.4. Building new logistic regression models

Sampling variation implies that different samples of fire injured trees lead to a different "best" models (Burnham et al., 2011) and the more combinations of variables we investigate for a fixed sample size, the more likely we are to identify erroneous suites of variables as important (Flack and Chang, 1987). Therefore, we did not investigate all possible combinations of variables for new models but selected suites of potential variables based on the examination of the distributions of the explanatory variables (Appendix A), the discriminatory ability of suites of variables in previously published models and our desire for a simple but broadly applicable model.

We identified suites of variables for new models in two ways and followed the same strategy for each tree species. First, we included the suites of variables used in each of the previously published models we tested. Some of these models contained complicated terms (such as cubic or squared terms or interactions). In an effort to identify parsimonious models we also tested suites of variables with related but simpler terms. We created simpler suites that contained only main effects if we also tested previously published suites that included interactions. We tested suites that contained only linear terms if we tested previously published suites that contained squared terms without linear terms. Ganio et al. (2015) noted that

Table 1
Summary of area under the receiver operating characteristic curve (AUC) for published logistic regression models applied to data from corresponding tree species and fire types.

Tree species	Fire type of source population (sample size in validation dataset)	Model source	Tested on source population subset of Oregon data		Tested on all trees of source species in Oregon data	
			95% CI for AUC	AUC	95% CI for AUC	AUC
PIPO	Rx Burning (1497)	Conklin and Geils (2008)	0.61–0.73	0.67	0.62–0.68	0.65
		Harrington and Hawksworth (1990)	0.63–0.74	0.69	0.63–0.70	0.66
		Saveland and Neuenschwander (1990)	0.46–0.59	0.52	0.55–0.62	0.58
		Stephens and Finney (2002)	0.62–0.73	0.68	0.64–0.70	0.67
		Thies et al. (2006)	0.67–0.77	0.72	0.66–0.72	0.69
PIPO	Wildfire (2528)	Finney (1999)	0.60–0.68	0.64	0.60–0.67	0.64
		Hood et al. (2010) (McNalley)	0.66–0.73	0.70	0.67–0.74	0.70
		Hood et al. (2010) (Cone)	0.72–0.79	0.75	0.73–79	0.76
		Keyser et al. (2006) (model 4)	0.62–0.70	0.66	0.59–0.66	0.62
		Keyser et al. (2006) (model 2)	0.63–0.71	0.67	0.61–0.68	0.64
		Regelbrugge and Conard (1993)	0.61–0.69	0.65	0.58–0.65	0.62
PIPO	Both (4025)	Hood et al. (2008)	0.75–0.80	0.77	0.75–0.80	0.77
		McHugh and Kolb (2003) (model 1)	00.65–0.71	0.68	0.65–0.71	0.68
		McHugh and Kolb (2003) (model 2)	0.64–0.71	0.68	0.64–0.71	0.68
PSME	Rx Burning (149)	Bevins (1980)	0.53–0.92	0.72	0.60–0.65	0.62
		Kobziar et al. (2006)	0.41–0.77	0.59	0.58–0.64	0.61
		Ryan and Reinhardt (1988)	0.57–0.88	0.72	0.76–0.80	0.78
PSME	Wildfire (3493)	Raymond and Peterson (2005)	0.78–0.82	0.80	0.77–0.81	0.80
		Ryan and Amman (1994)	0.54–0.59	0.57	0.53–0.59	0.56
PSME	Both (3642)	Hood et al. (2008)	0.80–0.84	0.82	0.80–0.84	0.82

variables whose distributions overlap for live and dead trees are not good discriminators. Our plots indicated that this was the case for the maximum height of bole scorch (BSH) and we noted the poor discriminatory ability of previously published models tested with our data. In an effort to reduce the number of models under consideration we chose to not use this variable.

We assessed support for each new model with the change in the AIC statistic (ΔAIC, Burnham et al., 2011) between the model in question and the model with the lowest AIC statistic. We always included a null model (no covariates) in the ranking. Models with ΔAIC statistics between 0 and 2–7 are considered to be equally well supported by the data (Burnham et al., 2011). We summarized the predictive ability of each model using a 10-fold cross-validated version of the AUC statistic and its 95% confidence interval (James et al., 2013). Cross-validation estimation fits the model using 90% of the data, estimates AUC with the withheld 10%, repeats this for each 10% subset and estimates the cross-validated AUC statistic from the multiple estimates from each subset. Cross-validation reduces bias that occurs when assessing predictive ability using data from which the model was built.

All analyses were carried out using PROC GENMOD and PROC LOGISTIC in SAS® Version 9.4 for Windows (copyright © 2013, SAS Institute Inc. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc., Cary, NC, USA).

2.3.5. Classification rates for model evaluation

A tree is classified as dead if the predicted probability of death from the regression model is greater than a predetermined decision criterion; we used a decision criterion of 0.5. We calculated the overall correct classification rate as the percent of correctly classified live and dead trees out of all classified trees and the overall error rate as the percent of incorrectly classified trees. We calculated sensitivity (percent of dead trees correctly predicted to be dead) and specificity (percent of live trees correctly predicted to be alive). We also calculated the correct mortality prediction rate as the percent of truly dead trees out of the total number of trees predicted to be dead and the incorrect live prediction rate as the percent of dead trees incorrectly predicted to be alive. The two types of misclassification errors, dead trees predicted as live (1-Sensitivity) or live trees predict as dead (1-Specificity), are inversely related. As the decision criterion increases, for example from 0.5 to 0.95, the number of live trees that are predicted to be dead decreases but the number of dead trees that are predicted to be alive increases. The decision criterion of 0.5 minimizes 1-Sensitivity and maximizes 1-Specificity.

We calculated classification rates for the Scott guidelines two ways. First, rates were obtained by classifying only those trees with a low probability of survival as dead. Secondly, we also classified a tree as dead if its score fell below the midpoint of the moderate probability of survival class. We used the latter method since Scott et al. (2002) assume that 50% of the moderate survival group will ultimately die from fire injury.

We calculated classification rates for our best Douglas-fir and best ponderosa pine logistic regression models and for the Malheur model. We calculated classification rates for these models applied to, prescription fire injured trees, wildfire injured trees, and all the trees in our dataset.

3. Results

3.1. Summary of field data by fire type and region

Ponderosa pine was present in northern Washington wildfires (688 trees) and prescribed fires (n = 719) and in eastern Oregon wildfires (n = 1840) and prescribed fires (n = 777). Out of the total 4024 ponderosa pine in our dataset, only 334 (8%) were dead after 3 years. Douglas-fir was present in the Griff fire (n = 59), northern Washington prescribed (n = 72) and wild fires (n = 149), eastern Oregon (n = 919) and southwestern Oregon wild fires (n = 2605). There are 3804 Douglas-fir trees in our sample and 535 (14%) were dead after 3 years.

Visual comparisons of the distributions for each variable among region and fire type did not indicate substantial differences, indicating that the role of each variable in any model would not change among regions (Ganio et al., 2015) for each tree species. Because of this, and because the sample size was not large for any single region for either species, we did not test models separately for each region. The distributions of fire injury variables within each region and fire type varied slightly (see Appendix A). Despite instructions to choose trees with some fire injury and green needles, 8 live ponderosa pine, 30 live Douglas-fir and one dead Douglas-fir showed no evidence of crown and bole injury. For ponderosa pine, 2411 live trees (65%) and 114 dead trees (5%) had no dead cambium samples, while 1835 live Douglas-fir trees (56%) and 148 dead Douglas-fir trees (28%) have no dead cambium samples.

3.2. Validation of previously published logistic regression models

The prediction of post-fire mortality for specific fire types using previously developed models was not consistently better than prediction for all trees regardless of the fire type for each species (Table 1). The overlap in 95% confidence intervals for AUC calculated from the subsets and from all trees indicates similar average discriminatory ability. The distribution summaries of fire injury variables for live and dead trees in our dataset are similar for both prescription and wild fire and thus models will discriminate between live and dead trees to the same degree regardless of fire type.

3.2.1. Ponderosa pine

Direct application of previously published models to trees from wildfire or prescription fire resulted in a wide range of discriminatory ability for ponderosa pine, from 52% to 77% (Table 1). The Hood 2008 model provided the best discriminatory ability (0.75–0.80) but models with similar suites of variables perform almost as well (e.g. Table 1: Hood et al., 2010). The Saveland and Neuenschwander (1990) model can do worse than random prediction (AUC: (0.46–0.59)).

Models that included a measure of crown damage typically did well (e.g. Table 1: Hood et al., 2008, 2010; Thies et al., 2006). Interestingly, models with bole scorch height in them (Conklin and Geils, 2008; Regelbrugge and Conard, 1993; Saveland et al., 1990) do not discriminate well and models that used the height or length of the crown that was scorched (e.g. Conklin and Geils, 2008; Keyser et al., 2006) did not do as well as those that used the proportion of crown volume that was damaged.

3.2.2. Douglas-fir

The most effective previously published model for Douglas-fir (Table 1: Hood et al., 2008) had an average discriminatory ability of more than 80% and both included percent of crown volume scorched, cambium kill rating and some measure of the presence of Douglas-fir beetle. Over all models, there was a wide range of average discriminatory ability (AUC), from slightly above 50% (Ryan and Amman, 1994) to over 80% (Hood et al., 2008). For some models (e.g., Kobziar et al., 2006; Ryan and Amman, 1994) the lower confidence limit indicates that the average discriminatory ability can be only slightly better than a coin toss. Our sample size of Douglas-fir from prescribed fire was small (149) so that the precision of the AUC from models originally created from prescription fires was poor but it increased when these models are applied to our larger sample of Douglas-fir.

All Douglas-fir models used DBH or a transformation of DBH (bark thickness in Reinhardt and Ryan, 1988; Ryan and Reinhardt, 1988; Ryan and Amman, 1994) and all models used a proportion of the crown volume that was damaged, except for Bevins (1980) which used the maximum height of the crown that was damaged. The discriminatory ability of the models using only bark thickness (calculated from DBH) and percent crown volume scorched (Ryan and Amman, 1994) was greatly improved when the cambium kill rating was included in the model (Raymond and Peterson, 2005).

3.3. New ponderosa pine logistic regression models

For both tree species, the ten-fold cross validated AUC and the ΔAIC statistic ranked models similarly (Tables 2 and 3). While ΔAIC ranks the support in the data for the model, we gave priority to the 10-fold cross-validated AUC statistic since our ultimate goal is correct classification. The best-supported new models for ponderosa pine (Models 1 and 2, Table 2) contains cambium kill rating, the presence of beetles and squared terms for the percent of crown volume scorched and have an average predictive ability of 80%. Model 2 contains a linear term for percent crown volume scorched but Model 1 does not. We tested Model 1 without the linear term in contrast to standard statistical practice (linear terms when higher order terms are also included), because it was the best suite of variables suggested by previously published models. However, the inclusion of the linear term allows curvature to be more general than what is described by its exclusion. Therefore, we suggest that Model 2 may be more appropriate since these models are used for prediction for new data sets in which the curvature may differ. The same model but without a squared percent crown volume scorch term (Model 3) was less well supported (ΔAIC = 15.61) but provided similar average discriminatory ability. Estimates of coefficients and 95% profile confidence intervals for model 2 are provided in Table 4.

Average predictive ability for single variable models range from 55% for DBH (Model 30) to 69% for cambium kill rating (Model 12). Single variable models predict, on average, as well as suites of multiple variables suggested by previous research. For example, Model 12 contains only cambium kill rating but discriminates on average as well as Model 23 (percent crown volume scorched, DBH) and Model 14 (the proportion of injured crown length and the bole scorch proportion). For our fire-injured trees, single variable models do not discriminate well but they do no worse than other more complex models.

The best-supported two-variable model (Table 2, Model 9) contains cambium kill rating and percent crown volume scorched (ΔAIC = 68.56) and has a relatively high average predictive ability of 77%. When an indicator of beetle presence is added to this set of variables the ΔAIC improves by approximately 35 units (68.56–33.20) for presence of red turpentine beetles (Model 6) and by approximately 51 units for the presence of beetles in the first 3 years (Model 3) but the predictive ability for these 3 variable models increases only slightly to 78% and 79% for presence of red turpentine beetle and presence of beetles in the first 3 years respectively. So while the presence of beetles increases the support

Table 2
Ten-fold cross-validated predictive ability (AUC), 95% confidence intervals and data support (ΔAIC) for ponderosa pine regression models using, % crown volume scorched (cvsperc), the number of tree quadrants with dead cambium (ckr), presence of mountain pine beetle, red turpentine beetle or Ips. sp. beetles 1–3 years post-fire (beetle3), the presence of red turpentine beetle 1 year post-fire (rtb1), the diameter at breast height in centimeters (dbhcm), the proportion of the crown height with scorched needles, maximum height of bole scorch as a proportion of tree height (bsp), bark thickness rating calculated from dbh (0.0376 + 0.0584 * DBH (inches), cvsperc/100 (cvsprop), % of crown length scorched (clsperc), % of the bole circumference that is charred (char), bole char severity rating (1–4) rating on the uphill side of tree (chups), indicator for the 90th and 100th percentile of the percent of crown length scorched (clsperc90, clsperc100 respectively), average bole scorch rating over 4 quadrants when bole scorch was present (bcc), indicator for 5th or 6th mistletoe rating (dmr4, dmr6 respectively).

Model ID	Ponderosa pine model Variables in model	Predictive 95% CI for 10-fold CV AUC	Ability 10-fold CV AUC	Model support Delta AIC
1	cvsperc^2 ckr beetle3	0.76–0.82	0.80	0.00
2	cvsperc cvsperc^2 ckr beetle3	0.77–0.82	0.80	0.55
3	cvsperc ckr beetle3	0.76–0.82	0.79	15.61
4	cvsperc cvsperc^2 ckr rtb1	0.75–0.81	0.78	16.60
5	cvsperc^2 ckr rtb1	0.76–0.81	0.78	16.66
6	cvsperc ckr rtb1	0.75–0.81	0.78	33.20
7	cvsperc ckr dbhcm rtb1	0.75–0.81	0.78	34.96
8	cvsperc cvsperc^2 ckr	0.74–0.80	0.77	53.07
9	cvsperc ckr	0.74–0.80	0.77	68.56
10	ckr beetle3	0.70–0.77	0.74	119.01
11	cvsperc cvsperc^2 beetle3	0.67–0.73	0.70	177.47
12	ckr	0.65–0.72	0.69	187.63
13	cvsperc beetle3	0.67–0.74	0.70	198.24
14	nsp bsp	0.65–0.72	0.69	240.43
15	cvsperc cvsperc^2	0.63–0.70	0.66	249.47
16	cvsperc cvsperc^2 dbhcm * cvsperc	0.62–0.69	0.66	250.75
17	cvsperc cvsperc^2 dbhcm	0.61–0.69	0.65	251.16
18	cvsperc cvsperc^2 dbhcm dbhcm * cvsperc	0.62–0.69	0.65	252.74
19	btf btf^2 cvsprop	0.5–0.71	0.69	259.57
20	dbhcm clsperc char	0.64–0.71	0.67	266.50
21	cvsperc chups	0.65–0.71	0.68	266.56
22	cvsperc	0.64–0.71	0.67	270.92
23	cvsperc dbhcm	0.64–0.70	0.67	272.70
24	cvsperc dbhcm * cvsperc	0.64–0.70	0.67	272.90
25	dbhcm clsperc dbhcm * clsperc	0.52–0.69	0.66	280.63
26	dbhcm clsclass dmr	0.61–0.68	0.64	287.23
27	clsperc90 claspec100 bcc^2 dmr5 dmr6	0.62–0.69	0.65	308.29
28	beetle3	0.56–0.63	0.59	325.52
29	dbhcm bshm	0.61–0.67	0.64	344.64
30	dbhcm	0.51–0.58	0.55	416.42
31	null	0.47–0.52	0.50	419.22

Table 3
Ten-fold cross-validated predictive ability (AUC), 95% confidence intervals and data support (ΔAIC) for Douglas-fir regression models using % crown volume scorched (cvsperc), diameter at breast height in centimeters (dbhcm), presence of Douglas-fir beetle 1–3 years post-fire (dfbar3), the number of tree quadrants with dead cambium (ckr), bark thickness (btr).

Model ID	Douglas-fir model Variables in model	Predictive 95% CI for 10-fold CV AUC	Ability 10-fold CV AUC	Model support Delta AIC within group
1	cvsperc cvsperc^2 cvsperc^3 ckr dbhcm dfbar3 dfbar3 * dbhcm	0.84–0.88	0.86	0.00
2	cvsperc cvsperc^2 cvsperc^3 ckr dbhcm dfbar3	0.84–0.88	0.86	13.29
3	cvsperc ckr dbhcm dfbar3 dfbar3 * dbhcm	0.84–0.88	0.86	26.64
4	cvsperc cvsperc^2 ckr dfbar3	0.84–0.89	0.86	28.73
5	cvsperc cvsperc^2 ckr dbhcm dfbar3	0.84–0.88	0.86	30.03
6	cvsperc ckr dfbar3	0.84–0.88	0.86	38.52
7	cvsperc ckr dbhcm dfbar3	0.84–0.87	0.86	39.71
8	cvsperc cvsperc^2 ckr	0.81–0.85	0.83	150.63
9	cvsperc cvsperc^2 ckr dbhcm	0.81–0.85	0.83	150.79
10	cvsperc ckr dbhcm	0.81–0.85	0.83	159.68
11	cvsperc ckr	0.81–0.85	0.83	159.70
12	cvsperc cvsperc^2 dfbar3	0.79–0.83	0.83	287.73
13	cvsperc cvsperc^2 dbhcm dfbar3	0.80–0.84	0.82	287.73
14	cvsperc cvsperc^3 dfbar3	0.79–0.83	0.81	289.55
15	cvsperc dbhcm dfbar3	0.80–0.84	0.82	296.46
16	cvsperc dfbar3	0.79–0.83	0.81	298.07
17	cvsperc cvsperc^2 dbhcm	0.77–0.81	0.79	405.67
18	btr cvsperc cvsper^2	0.76–0.81	0.79	405.68
19	cvsperc cvsperc^2	0.76–0.81	0.78	405.78
20	btr cvsperc	0.77–0.81	0.79	412.30
21	btr btr^2 cvsperc	0.76–0.80	0.78	412.62
22	cvsperc	0.76–0.81	0.78	413.02
23	dbhcm cvsperc	0.49–0.84	0.66	413.14
24	cvsperc dbhcm	0.76–0.81	0.79	413.14
25	btr cvsperc	0.77–0.81	0.79	413.14
26	btr btr^2 cvsperc	0.76–0.81	0.78	413.58
27	ckr dbhcm dfbar3	0.75–0.79	0.77	449.29
28	ckr dfbar3	0.73–0.78	0.75	449.98
29	ckr	0.67–0.73	0.70	637.06
30	ckr dbhcm	0.68–0.73	0.71	637.10
31	dfbar3 dbhcm	0.62–0.68	0.65	766.03
32	dfbar3	0.54–0.60	0.57	790.46
33	dbhcm cshft	0.6–0.65	0.62	900.13
34	dbhcm	0.54–0.59	0.56	954.47
35	null	0.47–0.52	0.50	977.07

Table 4
Estimated coefficients and 95% likelihood-profile confidence intervals (in square braces below estimates) in selected post-fire mortality logistic regression models. CVSperc is the percent of the crown volume killed, CKR is the number (out of 4) cambium samples that were dead, BEETLE3 is an indicator variable (0/1) for the presence of mountain pine beetle, red turpentine beetle and Ips in years 1–3, DFBAR3 is an indicator variable (0/1) for the presence of Douglas-fir beetle in years 1–3. A "–" indicates the variable was not used in that model. Model number refers to Model ID in Tables 2 and 3 for reference.

		Explanatory variable					
		Intercept	CVSperc	CVSperc^2	CKR	BEETLE3	DFBAR
Douglas-fir	Recommended model with cambium damage	−3.8824	0.0325	–	0.6757	–	2.2733
	(Model 6)	[4.11, −3.65]	[0.030, 0.035]		[0.59, 0.76]		[1.87, 2.68]
	Recommended model without cambium damage	−2.927	0.0148	0.00021	–	–	2.1282
	(Model 12)	[−3.12, −2.75]	[0.003, 0.026]	[0.0002, 0.00008]	–	–	[1.75, 2.51]
Ponderosa pine	Recommended model with cambium damage	−3.2657	−0.0083	0.00031	0.6356	0.0664	–
	(Model 2)	[−3.53, −3.001]	[−0.022, 0.005]	[0.002, 0.0005]	[0.54, 0.73]	[0.38, 0.64]	
	Recommended best model without cambium damage	−2.6016	−0.0102	0.00034		0.5652	
	(Model 11)	[−2.83, −2.38]	[−0.02, 0.0029]	[0.0002, 0.0005]		[0.44, 0.69]	

for the model, it produces only a slight change in average predictive ability. The inclusion of DBH in models for ponderosa pine did not improve the predictive ability or the support in the data.

3.4. New Douglas-fir logistic regression models

We identified a simple model that uses percent of crown volume scorched, cambium kill rating and the presence of Douglas-fir beetle in the first 3 years (Table 3, Model 6) as the recommended model for Douglas-fir. Eighteen of the 35 tested Douglas-fir models had an average predictive ability (AUC) greater than 80% but they varied widely in complexity. In a predictive setting, simple models with good discrimination may be preferred over complicated models (James et al., 2013). Therefore, we prefer the simple model over more complex models with more terms or interactions since the average discriminatory ability does not increase with model complexity. Estimates of coefficients and 95% profile-likelihood confidence intervals are provided in Table 4.

Table 5
Classification table and prediction percentages from the Scott guidelines.

Overall correct classification (%)	Overall error rate (%)	Sensitivity (%)	Specificity (%)	Correct mortality prediction rate (%)	Incorrect live prediction rate (%)	Number observed dead	Number observed alive	Total number	Prediction category
Ponderosa pine 3 year post fire mortality only trees with low probability of survival classed as dead									
<53.34 cm DBH						0	0	0	Dead
						262	2582	2844	Alive
90.8	9.2	0.0	100.0	–	9.2	262	2582	2844	Total
⩾53.34 cm DBH						0	0	0	Dead
						126	1054	1180	Alive
89.3	10.7	0.0	100.0	–	10.7	126	1054	1180	Total
Ponderosa pine 3 year post fire mortality; trees scoring below midpoint of moderate survival classed as dead									
<53.34 cm DBH						4	45	49	Dead
						258	2537	2795	Alive
89.3	10.6	1.5	98.3	8.1	9.2	262	2582	2844	Total
>53.34 cm DBH						0	15	15	Dead
						126	1039	1165	Alive
88.0	11.9	0	98.6	0	10.8	126	1054	1180	Total
Douglas-fir 3 year post-fire mortality; trees with low probability of survival classed as dead									
<50.8 cm DBH						10	82	92	Dead
						216	1595	1811	Alive
84.3	15.6	4.4	95.1	10.9	11.9	226	1677	1903	Total
⩾50.8 cm DBH						0	18	18	Dead
						255	1628	1883	Alive
85.6	14.4	0.0	98.9	0.0	13.5	255	1646	1901	Total
Douglas-fir 3 year post fire mortality; trees scoring below midpoint of moderate survival classed as dead									
<50.8 cm DBH						48	356	404	Dead
						178	1321	1499	Alive
71.9	28.0	21.2	78.9	11.9	11.9	226	1677	1903	Total
⩾50.8 cm DBH						25	167	192	Dead
						230	1479	1709	Alive
79.1	20.9	9.8	89.9	9.8	13.4	255	1646	1901	Total

Overall correct classification: (# Observed dead & predicted dead + # Observed alive & predicted alive)/Total # of trees.
Overall error rate: (# Observed dead & predicted alive + # Observed alive & predicted dead)/Total # of trees.
Sensitivity: (# Observed dead & predicted dead/Total # of dead trees); Specificity: (# Observed live & predicted live/Total # of live trees).
Correct mortality prediction rate: (# Observed dead & predicted dead/Total # of predicted dead trees); Incorrect Live prediction rate: (# Observed dead & predicted alive/Total # of predicted alive trees).

In contrast to ponderosa pine, the best single-variable model uses percent crown volume scorched, and not cambium kill rating (Table 3, Model 22). Although the predictive ability of this model is 78% (95% CI [0.76–0.81]) it is not well supported (ΔAIC = 413.02); it is ranked 22nd in our set of 35 models.

The 2-variable model with cambium kill rating and percent crown volume scorched (Table 3, Model 11) has much greater support than any one-variable model (ΔAIC = 159.7) and the predictive ability is 83%. The addition of DBH to this 2 variable model (Model 9) does not increase the support in the data. However, when a measure of the presence of Douglas-fir beetle in the first three years is included (Model 6), support improves by 121 units (159.7–38.52) and predictive ability increases to 86% [0.84, 0.88]. The addition of a squared term for percent crown volume scorched to the 3-variable model of cambium kill rating, percent crown volume scorched and the presence of Douglas-fir beetle in the first 3 years improved the support (Model 4, ΔAIC = 28.73).

All of the previously published suites of variables for Douglas-fir contained DBH or its transformation, bark thickness. We tested a number of models that did not include DBH and two of the 8 best supported models did not include DBH (Models 4 and 6). The addition of DBH to these two models did not improve the support for the model (e.g. compare Model 4 with Model 5).

The best supported set of variables (Model 1) was originally proposed by Hood et al. (2008) and includes cambium kill rating, DBH, presence of Douglas-fir beetle, linear, quadratic and cubic terms for percent crown volume scorched and allows the effect of DBH to differ between the presence or absence of Douglas-fir beetle. We included simpler variants of this set of variables in our set of models to assess the degree to which the more complicated model was warranted. The average predictive ability of the nine best supported models have high, and identical predictive ability of about 86% (95% CI is [0.84–0.88]) although the ΔAIC ranged from 13.29 to 68.56. Since large ΔAIC values (>20) indicate the potential for bias and models that fit well are not necessarily good discriminators (Ganio et al., 2015), our results suggest that models with some bias may still discriminate well. In particular, simple models that don't include DBH, the interaction of DBH with beetle presence, or squared or cubic terms provide equivalent average discrimination compared to those that do. For these reasons we recommend using the simplest model with the highest predictive ability.

3.5. Classification rates for Scott guidelines

In general, the Scott guidelines correctly classified live trees but did poorly when classifying dead trees (Table 5). When only the trees that fell into the lowest probability of survival category were classified as dead, the Scott guidelines did not correctly classify any dead trees but correctly classified all live trees. When the mid-point of the "Moderate" class was used, 1.5% of dead trees <53.34 cm DBH, were correctly predicted dead and 98.3% of live trees <53.34 DBH were correctly predicted alive (Table 5). For ponderosa pine $\geqslant$53.34 cm DBH, no dead trees were correctly predicted as dead but 98.6% of live trees were correctly predicted as live.

When the "Low" probability of tree survival was used as a cutoff for Douglas-fir, the Scott guidelines accurately classified approximately 95% of live trees <50.8 cm DBH and correctly classified 4.4% of dead trees (Table 5). When the mid-point of the Moderate class was used as a cutoff for 3-year mortality, 21.2% of dead trees and 78.9 of live Douglas-fir <50.8 cm DBH were correctly classified. For Douglas-fir $\geqslant$50.8 cm DBH, 9.8% of dead trees and 89.9% of live trees were correctly classified.

3.6. Classification and error rates for recommended logistic regression models

Comparison of the classification and error rates for our best models (Table 6) and for the Malheur model applied to prescription fire injured trees only, wildfire injured trees only and all injured trees yield similar error rates. Therefore, we present and discuss error rates for trees from both fire types combined.

3.6.1. Ponderosa pine

For ponderosa pine, the overall correct classification rates (Table 6) are high and similar for the Malheur model (89%) and our model (92%). Both models do well at correctly classifying live trees (specificity) with the Malheur model doing slightly less well (95%) than our model (99.2%). But both models do a poor job of correctly classifying dead trees (sensitivity is low) but the Malheur model (23.7%) does slightly better than our model (12.3%). Of all trees predicted to be dead, less than a third are truly dead under the Malheur model (29.8%) and slightly more than half (58.6%) are truly dead under our model. That is, predictions of dead trees

Table 6
Ponderosa pine and Douglas-fir classification and prediction percentages from recommended logistic regression models, using a decision criterion of 0.5, for all trees.

Overall correct classification (%)	Overall error rate (%)	Sensitivity (%)	Specificity (%)	Correct mortality prediction rate (%)	Incorrect live prediction rate (%)	Number observed dead	Number observed alive	Total number	Prediction category
Ponderosa pine Malheur model (Thies et al., 2006) Wild and prescription fires						79	186	265	Predicted dead
						255	3504	3759	Predicted alive
89.0	11.0	23.7	95.0	29.8	6.8	334	3690	4024	Total
Ponderosa pine Model #1 Wild and prescription fires						41	29	70	Predicted dead
						293	3661	3954	Predicted alive
92.0	8.0	12.3	99.2	58.6	7.4	334	3690	4024	Total
Douglas-fir Model #6 Wild and prescription fires						190	83	273	Predicted dead
						345	3186	3531	Predicted alive
88.7	11.3	35.5	97.5	69.6	9.8	535	3269	3804	Total

Overall correct classification: (# Observed dead & predicted dead + # Observed alive & predicted alive)/Total # of trees.
Overall error rate: (# Observed dead & predicted alive + # Observed alive & predicted dead)/Total # of trees.
Sensitivity: (# Observed dead & predicted dead/Total # of dead trees); Specificity: (# Observed live & predicted alive/Total # of live trees).
Correct mortality prediction rate: (# Observed dead & predicted dead/Total # of predicted dead trees); Incorrect Live prediction rate: (# Observed dead & predicted alive/Total # of predicted alive trees).

from our model are more likely to be correct than predictions from the Malheur model. Of all trees predicted to be alive, 6.8% are actually dead under the Malheur model while 7.4% are mistakenly classified under our model.

3.6.2. Douglas-fir

Our model correctly classifies 88.7% of all trees; 97.5% of all live trees are correctly classified but only 11.3% of dead Douglas-fir are correctly classified (Table 6). Of all Douglas-fir predicted to be dead, 69.9% are actually dead and 9.8% of Douglas-fir classified as live by the model are actually dead. The general result for Douglas-fir is similar to ponderosa pine; the models do best at correctly predicting live trees but do poorly when classifying dead trees.

For both tree species, the overall high correct classification rates are driven by the correct classification of live trees. These results are in agreement with the visual examination of the distributions of the explanatory variables (Appendix C) which show significant overlap between dead and live trees. For managers seeking to apply these models to correctly predict mortality and survival, it is important to note that using AUC, without looking at the error rates could lead one to believe that a model is a good discriminator for both live and dead trees – but that might not be the case.

4. Discussion

4.1. Previous models

The previously published models predicting Douglas-fir and ponderosa pine tree mortality are most accurate when they contained measures of crown volume, cambium damage and the presence of beetles. For ponderosa pine, the top performing model (Hood et al., 2010) outperformed the Malheur model (Thies et al., 2006) even though the Malheur model was developed and tested on fire-injured trees in the Pacific Northwest. The Malheur model for ponderosa pine was previously validated on a sample of 10,109 fire-injured trees (Thies and Westlind, 2012) where 65% of dead trees were correctly classified as dead and 80% of all trees predicted to be dead were actually dead. The trees in our dataset were larger in diameter than those from which the Malheur model (Thies et al., 2006) was built and this may account for the difference in discrimination.

To our knowledge the Scott guidelines have not been widely validated except for what we report here. The Scott guidelines and our logistic regression models resulted in similar error rates and classification ability. In general, the large proportion of live trees in our dataset demonstrated a wide range of values for the fire injury variables and there were live trees with significant amounts of fire injury. This resulted in low error rates (<10%) when classifying live trees but very large error rates (>80%) when classifying dead trees. In general, the logistic regression models slightly outperformed the Scott guidelines when classifying dead trees but both models correctly classified live trees about 90% of the time.

4.2. Best new predictive models

The bests sets of predictive variables for new models were similar to those in the best previously published models. For ponderosa pine, models that included percent of crown volume scorched, cambium kill rating and the presences of beetles outperformed models without these variables and the model is improved with the addition of a squared term for the percent of crown volume scorched, indicating curvature. For Douglas-fir, many new models produced high and similar predictive ability. In addition, some but not all, of the top models for Douglas-fir contained DBH. The top two best supported Douglas-fir models contained cubic terms for crown volume scorched, DBH and interaction between DBH and the presence of beetles. However, much simpler models, without interactions, DBH or cubic terms had the same high predictive ability (86%) for Douglas-fir. Since predictive models are to be applied to new and independent samples of trees, models with specialized curvature may be over-fit to our sample. We resort to the principle of parsimony and recommend the simple models.

Our results corroborate previous research from other regions where tree crown fire injury and cambium injury are consistently useful in the prediction of post-fire tree mortality investigation (Hood et al., 2008, 2010; Thies and Westlind, 2012). Many previously published models for ponderosa pine used DBH but this variable did not add to the discriminatory ability for our data. Some previously published Douglas-fir models used more than three explanatory variables or relied on interactive terms (Hood et al., 2008; Hood and Bentz, 2007). Our models with similar suites of variables have the same discriminatory ability as simpler models suggesting that interaction terms are not necessary for good discrimination. For ponderosa pine, our recommended model is more complex than a previously published model (Hood et al., 2008) in that it incorporates linear and quadratic crown scorch terms to model curvature more generally. For Douglas-fir, we recommend a model that is simpler than previously published models (Hood et al., 2008; Hood and Bentz, 2007) but which discriminates just as well.

Measuring cambium damage is time-consuming and other authors have considered models without this variable (e.g. Thies et al., 2006). In our investigation, for both tree species, models without cambium damage had much less model support and had lower discriminatory abilities indicating a trade-off between expense and accurate discrimination. Practitioners may want to assess the reduction in measurement expense compared to the increase in incorrect prediction rates. Depending on the situation, the reduction in field costs may offset the increase in prediction error (either correct mortality rate or incorrect prediction rate) and thus make the use of a model without cambium damage advantageous. For Douglas-fir, the Ryan and Reinhardt model (Ryan and Reinhardt, 1988) does not use cambium damage (only crown damage and DBH via the linear transformation to bark thickness) and has been extensively used in management settings (Lutes, 2016). Although this model was not highly ranked, it did provide reasonable average discriminatory ability of 76–80%. But models that include cambium damage can significantly improve the discrimination.

4.3. Error rates

The error rates for the Scott guidelines and our logistic regression models were similar. In general, a large proportion of our live trees demonstrated a wide range of fire injury and live trees had significant amounts of fire injury. This resulted in low error rates when classifying live trees but high error rates (>80%) when classifying dead trees. In general, the logistic regression models slightly outperformed the Scott guidelines when classifying dead trees but both models correctly classified 90% of live trees and about 10% of dead trees.

Hood et al. (2010) noted that statistical models should be used in concert with other considerations for stand management, emphasizing that error rates change as decision criteria change. No matter what rule or model is used, the classification of a continuous probability into individual (binary) tree mortality will always incur the types of errors described in Table 6. Therefore, land managers would be well-served to develop an understanding of the trade-offs between specificity and sensitivity and the more practical trade-offs between the correct mortality prediction rate and the correct survival prediction rate. For example, in salvage operations, managers must assess the relative cost of predicting a dead tree as live (resulting in a loss of revenue) versus predicting a live tree as dead (resulting in salvage logging of live trees). On the other hand, in a campground, mistakenly predicting a dead tree as alive may be a significant safety risk and far outweigh the risk of removing a potential live tree. In the first case, minimizing the incorrect prediction of live trees may be most important while in the second case, minimizing the incorrect prediction of dead trees may be most important. While choosing a standard decision criterion such as 0.5 is helpful to compare models, the application of the model could include a choice of the decision criterion based on the costs of the errors (Hand, 2009).

4.4. Ramifications of tree sampling protocol

The tree sampling protocol can affect the error rates and discriminatory ability of the model. Hood et al. (2010) deliberately selected a balanced sample of fire-injured trees along a range of fire injury that included high and low levels of injury; Thies and Westlind (2012) obtained an unbiased sample of trees from within areas of moderate fire severity where tree crowns were not totally consumed but where there was evidence of fire in the understory. Sampling the entire distribution of fire injury allows the range of a fire-injury variable for dead trees to extend beyond the range for live trees and potentially separate the distributions of the variable between live and dead trees resulting in a high proportion of accurately predicted live or dead trees (Ganio et al., 2015). The discrepancy between previously reported low error rates for the Malheur model (Thies et al., 2006; Thies and Westlind, 2012) and the high error rates from our data may be due to differences in sampling. Since our sampling protocol did not prescribe that trees with little and lethal fire injury be sampled, we are more likely to find the distributions of a discriminating variable to overlap between live and dead trees increasing the likelihood that a dead tree is classified as alive. Our sampling protocol was chosen to replicate the management scenario where management personnel cannot identify trees as clearly alive or dead. But a small proportion of our trees ultimately died; 8.3% for ponderosa pine (compared to 88% in Hood et al., 2010 and 16% in Thies and Westlind, 2012) and 14.3% for Douglas-fir (compared to 39% in Hood et al., 2007b) and the range of fire injury for trees which survive for 3 years is surprisingly wide.

Individual tree selection was determined by field personnel. The lack of specific criteria for transect or tree selection within a fire suggest the possibility that field crews unknowingly biased the sample toward live trees. The site selection criterion of no planned post-burn activities could also have biased our samples toward live trees if post-burn management is more likely in higher severity fires. Cambium damage is a good indicator of potential tree mortality but our data suggest that within the region and fires that we sampled, trees can live even with significant amounts of cambium damage. In practice, it is this middle range of external tree injury where classification will be difficult and where a measure of significant internal damage (such as a cambium injury rating of 3) can improve classification.

5. Conclusions

Our new models for Oregon and Washington and the validation of existing models for Douglas-fir and ponderosa pine suggest that the percent of the crown volume scorched and the cambium kill rating are good predictors of post-fire tree mortality for both tree species. The presence of beetles in year 3 improves the average predictive ability and is present in our recommended model. For Douglas-fir, models that included these variables had average predictive ability above 80% but for ponderosa pine, average predictive ability is not above 80% suggesting that it can be more difficult to identify dying ponderosa pine trees.

The two types of errors that can occur (i.e., falsely predicting a dead tree will live and falsely predicting a live tree will die) come with different costs to land managers that depend on the application. Land managers using a model to predict mortality may wish to change the decision criterion for a particular application from the typical 50% to something higher in order to control the costliest error in their application.

Since statistical models are subject to sampling variation the estimated coefficients in logistic regression models can vary due to the particular trees that were included in the sample. Models may have different coefficients and still yield similarly accurate classifications of post-fire mortality. A practical prudent approach to the prediction of post-fire tree mortality could be to identify multiple models that use similar variables and apply the models to the trees needing classification. Trees for which there is some disagreement among models may need closer examination and trees for which multiple models provide the same classification may be more likely to be accurately classified.

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Appendix A. Characterization of fires

See Tables A1 and A2.

Table A1
Fire name, year of fire, fire location (latitude, longitude) and average annual rainfall for the location of fire.

Fire	Year	Latitude, longitude	Annual average (inches)
Apple	2002	43.25357, −122.69198	54.33
B & B Complex	2006	44.4971418, −121.7626360	52.76
Biscuit	2002	42.32976479, −123.6620449	105.91
Blossom	2006	42.7794056, −123.9528139	96.46
Bonanza	2004	45.001220, −121.992419	94.49
Bull Spring	2003	44.616541, −119.007998	21.65
Clark	2003	44.047347, −122.698135	59.06

(continued on next page)

Table A1 (*continued*)

Fire	Year	Latitude, longitude	Annual average (inches)
Columbia Complex	2007	46.277028, −117.756792	33.86
Davis Lake	2003	43.620914, −121.772224	38.58
Egley	2007	43.727393, −119.390993	20.08
Fischer	2004	47.580467157, −120.5646950	24.8
Grapple	2007	44.028851, −119.173970	23.23
Griff	2003	47.876519, −123.540838	58.27
Herman Creek	2003	45.684939, −121.784611	101.57
Hud2	2005	48.3854722, −119.2580028	12.6
Monument	2007	44.569175, −119.535190	14.96
Nile	2004	46.85748228, −121.004983264	27.95
Pearrygin Creek	2005	48.505384321, −120.1336373	15.75
School	2005	46.272495851, −117.6039655	20.47
Shake Table	2007	44.2963639, −119.2479639	21.65
Sisters	2006	44.3249278, −121.6176389	14.57
Squaw Creek	2005	48.103181971, −120.1175468	22.44
Tiller Complex	2009	43.10296367, −122.8549645	50.79

Table A2
Summary of tree data by tree species and fire. Mean, minimum and maximum values of diameter at breast height (DBH), percent of crown volume scorched (%CVS, by volume), proportion of needles that are scorched (NSP) and the proportion of the bole that is scorched (BSP).

Type	Region	Fire	# Trees	Mean DBH	Min DBH	Max DBH	Mean % CVS	Min % CVS	Max % CVS	Mean NSP	Min NSP	Max NSP	Mean BSP	Min BSP	Max BSP
Ponderosa pine															
RX	N WA	Nile	273	33.1	15.7	82.0	50.0	5.0	98.0	0.36	0.00	1.00	0.21	0.01	0.75
RX	E OR	Sisters	784	55.2	13.0	109.2	31.5	0.0	95.0	0.29	0.00	1.00	0.14	0.00	0.78
RX	N WA	SquawCreek	446	37.2	15.5	60.5	44.9	0.0	95.0	0.39	0.00	1.00	0.21	0.01	0.57
WILD	SW OR	Biscuit	11	58.4	12.7	91.4	2.6	0.0	29.0	0.02	0.00	0.27	0.08	0.02	0.14
WILD	E OR	B&B	613	53.1	18.3	119.4	27.2	0.0	100.0	0.25	0.00	1.00	0.23	0.00	0.94
WILD	E OR	BullSpring	113	54.2	16.8	96.3	22.4	0.0	100.0	0.11	0.00	1.00	0.16	0.00	0.88
WILD	E OR	Columbia	174	55.2	17.8	114.3	15.5	0.0	99.0	0.15	0.00	1.00	0.18	0.00	0.61
WILD		DavisLake	429	64.1	18.0	125.0	45.7	0.0	99.0	0.41	0.00	1.00	0.27	0.01	0.83
WILD	E OR	Egley	527	50.6	17.8	99.1	23.7	0.0	99.0	0.22	0.00	1.00	0.13	0.00	0.75
WILD	N WA	Fischer	118	40.2	21.3	71.9	37.5	0.0	90.0	0.30	0.00	0.82	0.25	0.02	0.72
WILD	E OR	Grapple	137	57.8	20.3	99.1	16.9	0.0	99.0	0.18	0.00	0.96	0.10	0.01	0.84
WILD	N WA	Hud2	216	44.1	17.5	115.3	14.0	0.0	95.0	0.13	0.00	0.94	0.15	0.01	0.54
WILD	E OR	Monument	433	40.6	20.3	114.3	11.5	0.0	95.0	0.10	0.00	1.00	0.12	0.00	1.00
WILD		Pearrygin	356	43.7	19.3	77.0	48.3	0.0	95.0	0.42	0.00	0.96	0.25	0.03	0.67
WILD	E OR	School	466	39.2	18.8	106.2	16.5	0.0	95.0	0.16	0.00	0.95	0.14	0.00	1.00
WILD	E OR	ShakeTable	45	70.3	38.1	121.9	8.0	0.0	58.0	0.10	0.00	0.67	0.13	0.00	0.51
WILD	SW OR	TillerCo	20	51.1	21.6	125.0	25.6	0.0	83.0	0.25	0.00	0.83	0.05	0.00	0.13
Douglas-fir															
RX	N WA	Nile	91	40.3	21.1	94.0	47.0	0.0	90.0	0.26	0.00	1.00	0.20	0.05	0.56
RX	N WA	SquawCreek	59	38.1	18.5	61.0	28.3	0.0	95.0	0.22	0.00	0.82	0.15	0.04	0.66
WILD	SW OR	Apple	273	70.7	12.7	170.2	13.9	0.0	93.0	0.14	0.00	0.94	0.16	0.00	0.94
WILD	SW OR	Biscuit	530	55.8	12.7	203.2	31.3	0.0	99.0	0.31	0.00	0.98	0.18	0.00	0.65
WILD	SW OR	Blossom	261	56.6	14.0	130.3	5.7	0.0	80.0	0.06	0.00	0.80	0.18	0.00	0.95
WILD	E OR	BnB	310	54.7	21.6	135.1	17.0	0.0	95.0	0.15	0.00	1.00	0.16	0.00	0.61
WILD		Bonanza	101	42.5	22.9	110.2	24.4	0.0	100.0	0.22	0.00	1.00	0.17	0.00	0.40
WILD	E OR	BullSpring	77	40.9	15.5	102.9	37.6	0.0	100.0	0.24	0.00	1.00	0.19	0.00	1.05
WILD	SWOR	Clark	705	72.5	14.7	210.8	23.5	0.0	99.0	0.21	0.00	1.00	0.17	0.00	0.79
WILD	E OR	Columbia	234	51.8	15.2	137.2	27.0	0.0	99.0	0.26	0.00	1.00	0.15	0.00	0.66
WILD		DavisLak	65	62.3	23.4	126.0	39.8	0.0	100.0	0.34	0.00	1.00	0.26	0.01	0.48
WILD	N WA	Fischer	72	46.3	28.4	80.0	40.0	0.0	90.0	0.28	0.00	0.88	0.30	0.00	0.89
WILD	E OR	Grapple	44	56.2	10.2	124.5	46.8	0.0	99.0	0.37	0.00	0.91	0.20	0.00	1.00
WILD		Griff	59	53.7	26.9	110.0	4.2	0.0	99.0	0.11	0.00	1.00	0.09	0.01	0.43
WILD		HermanCr	371	52.8	19.1	111.3	20.4	0.0	99.0	0.17	0.00	0.83	0.13	0.01	0.47
WILD	N WA	Hud2	8	57.9	34.3	79.5	15.1	0.0	80.0	0.14	0.00	0.56	0.21	0.12	0.27
WILD	E OR	Monument	11	42.9	30.5	96.5	12.3	0.0	40.0	0.20	0.00	0.69	0.19	0.07	0.36
WILD	N WA	Pearrygi	6	49.1	43.7	58.4	36.0	1.0	60.0	0.32	0.00	0.70	0.13	0.01	0.18
WILD	E OR	School	130	38.2	18.0	80.8	15.1	0.0	90.0	0.16	0.00	0.85	0.12	0.00	0.53
WILD	E OR	ShakeTable	173	58.3	15.2	137.2	26.9	0.0	95.0	0.27	0.00	1.00	0.20	0.00	0.75
WILD	SW OR	TillerCo	306	60.9	15.5	163.8	12.2	0.0	95.0	0.12	0.00	0.94	0.12	0.00	0.75

Appendix B. Descriptions of previously published models

See Tables B1–B6.

Table B1
Descriptions of cited models used to test data from ponderosa pine prescription fires.

Model	Yrs post fire	Region	# Fires	# Trees	Model	Variable	Calculation from our data
Conklin and Geils (2008)	3	NM	6	1585	P_m = 1/[1 + exp(−(−4.4610 + 1.6827 (CLSperc90) + 3.5171(CLSperc100) + 0.2779 (BCC^2) + 0.8455(DMR5) + 2.3453(DMR6)))]	CLSperc90	Indicator variable (0/1) crown scorch length of 90%
						CLSperc100	Indicator variable (0/1) crown scorch length of 100%
						BCC	Average bole scorch rating over 4 quadrants when bole scorch was present
						DMR5	Indicator variable (0/1) for dwarf mistletoe rating = 5
						DMR6	Indicator variable (0/1) for dwarf mistletoe rating = 6
Harrington and Hawksworth (1990)[a]	1	AZ	1	191	P_m = 1/[1 + exp(−(−4.91 − 0.10(DBHin) + 0.10(CLSclass) + 0.29(DMR))]	DBHin	Diameter at breast height in inches
						CLSclass	Percent of crown length scorched, classified into quartiles (0, 25, 50, 75, 100)
						DMR	Dwarf mistletoe rating
Saveland and Neuenschwander (1990)	1	ID	21	194	P_m = 1/[1 + exp(−2.33 + 0.37(DBHcm) − 0.36(BSHm))]	DBHcm	DBH (cm) in 5 cm classes
						BSHm	Max. crown scorch height (m)
Stephens and Finney (2002)	3	CA	1	170	P_m = 1/[1 + exp(−(−3.155 − 0.0410(DBHcm) + 0.0550(CVSperc)))]	DBHcm	Diameter at breast height (cm)
						CVSperc	Estimated crown volume scorch (%)
Thies et al. (2006)	4	NE OR	6	3415	P_m = 1/[1 + exp(−(−4.4635 + 3.3328(NSP) + 6.6203(BSP)))]	NSP	Proportion of damaged crown length based on scorched needles
						BSP	Maximum bole scorch height as a proportion to tree height (same as Regelbrugge and Conard, 1993)

P_m = probability of mortality.
[a] In the published article (Harrington and Hawksworth, 1990), the initial minus sign that precedes the linear predictor in the formula is missing. However, using that published model gives an AUC statistic of <50%. This suggests that there is an error in the publication and for this analysis an initial minus sign was included.

Table B2
Descriptions of cited models used to test data from ponderosa pine wild fires.

Model	Yrs post fire	Region	# Fires	# Trees	Model	Variable	Calculation from our data
Finney (1999)	4	MT	3	1750	P_m = 1/[1 + exp(6.411(BT) − 4.891 (BT^2) − 5.799(CVSprop))]	BT	BT (in) = −0.0376 + 0.0584 * DBH (inches) (Ryan, 1982)
						CVSprop	Crown volume killed (0–1)
Hood et al. (2010) (Cone)	5	CA	1 (Cone)	926	P_m = 1/[1 + exp(−(−5.4174 + 0.000966 (CVSperc^2) + 0.8160(CKR) + 1.0483(RTB1)))]	CVSperc	Crown volume killed (%)
						CKR	Number (out of 4) dead cambium samples (Ryan, 1982)
						RTB	Presence (1) or absence (−1) of red turpentine beetle in year 1
Hood et al. (2010) (McNally)	5	CA	1 (McNally)	1079	P_m = 1/[1 + exp(−(−6.3501 + 0.0759 (CVSperc) + 0.2052(CKR) + 0.0455(DBHcm) + 1.1866(RTB1)))]	DBHcm	Diameter at breast height (cm)
						CVSperc	Crown volume killed (%)
						CKR	Number (out of 4) dead cambium samples (Ryan, 1982)
						RTB1	Indicator variable (0/1) for presence of red turpentine beetle in year 1
Keyser et al. (2006) (model4)	5	SD	1	721	P_m = 1/[1 + exp(−(−0.237 − 0.098(DBHcm) + 0.027(CLSperc) + 0.022(CHAR)))]	DBH	Diameter at breast height (cm)
						CLSperc	Crown length killed (%)
						CHAR	Bole circumference charred (%).
Keyser et al. (2006) (model 2)	5	SD	1	721	P_m = 1/[1 + exp(−(−1.104 − 0.156(DBHcm) + 0.013(CLSperc) + 0.001(DBH * CLSperc)))]	DBHcm	Diameter at breast height (cm)
						CLSperc	Crown length killed (%)
						DBH * CLSperc	Interaction of DBHcm an CLSperc
Regelbrugge and Conard (1993)	2	CA	1	825	P_m = 1/[1 + exp(−(1.0205 − 0.0933(DBHcm) + 0.2858(BSHm)))]	DBHcm	Diameter at breast height (cm)
						BSHm	Length from ground to highest point of bole char (m)

Table B3
Descriptions of cited models used to test data from ponderosa pine prescription and wild fires combined.

Model	Yrs post fire	Region	# Fires	# Trees	Model	Variable	Calculation from our data
Hood et al. (2008)	3	W USA	13	4115	P_m = 1/[1 + exp(−(−4.1914 + 0.000376(CVSperc^2) + 0.5130 (CKR) + 1.5873(BEETLE3)))]	CVSperc	Crown volume killed (%)
						CKR	Number (out of 4) dead cambium samples (Ryan, 1982)
						BEETLE3	Presence (1) or absence (−1) of mountain pine beetle, red turpentine beetle and Ips in years 1–3
McHugh and Kolb (2003) (model1)	3	AZ	3	1367	P_m = 1/[1 + exp(−(−9.7149 + 0.0921(TCD) + 0.8082(CHUPS)))]	TCD	Crown volume killed (%)
						CHUPS	Bole char severity rating (0–4) on uphill side
McHugh and Kolb (2003) (model2)	3	AZ	3	1367	P_m = 1/[1 + exp(−(−8.7456 + 0.0128(DBHcm) + 0.0960(TCD)))]	DBHcm	Diameter at breast height (cm)
						TCD	Crown volume killed (%)

Table B4
Descriptions of cited models used to test data from Douglas-fir prescription fires.

Model	Yrs post fire	Region	# Fires	# Trees	Model	Variable	Definition
Bevins (1980)	1	MT	1	176	P_m = 1/[1 + exp(−0.1688 + 0.3174(DBHin) − 0.09321(CSHft))]	DBHin	Diameter at breast height (inches)
						CSHft	Max. crown height that was killed (ft)
Kobziar et al. (2006)	1	CA	3	163	P_m = 1/[1 + exp(−(4.2076 − 0.2979(DBHcm) + 0.0359(TCD)))]	DBHcm	Diameter at breast height (cm)
						TCD	Crown volume killed (%)
Ryan and Reinhardt (1988)	3	PNW	43	1488	P_m = 1/[1 + exp(0.1344 + 0.9407(BT) − 0.0690(BT^2) − 0.00542(CVSperc^2))]	BT	BT (cm) = 0.065 * DBHcm (Monserud, 1979)
						CVSperc	Estimated crown (foliage and bud) volume killed (%)

Table B5
Descriptions of cited models used to test data from Douglas-fir wild fires.

Model	Yrs post fire	Region	# Fires	# Trees	Model	Variable	Definition
Raymond and Peterson (2005)	2	OR	1	244	P_m = 1/[1 + exp(−(−1.540 − 0.079(DBHcm) + 0.062(CVSperc) + 1.348(CKR)))]	DBHcm	Diameter at breast height (cm)
						CVSperc	Crown volume killed (%)
						CKR	Number (out of 4) dead cambium samples (Ryan, 1982)
Ryan and Amman (1994)	3	WY	4	125	P_m = 1/[1 + exp(−1.941 + 6.316(1−exp(−0.3937 (BT))) − 0.000535(CVSperc^2))]	BT	BT (cm) = 0.065 * DBHcm (Monserud, 1979)
						CVSperc	Crown volume killed (%)

Table B6
Descriptions of cited models used to test data from Douglas-fir prescription and wild fires combined.

Model	Yrs post fire	Region	# Fires	# Trees	Model	Variable	Definition
Hood et al. (2008)	3	W USA	10	1409	P_m = 1/[1 + exp(−(−1.8912 + 0.07(CVSperc) + 0.0019(CVSperc^2) + 0.000018(CVSperc^3) + 0.5840(CKR) − 0.031(DBHcm) − 0.7959(DFBAR3) + 0.0492(DBHcm * DFBAR3)))]	DBHcm	Diameter at breast height (cm)
						CVSperc	Crown volume killed (%)
						CKR	Number (out of 4) dead cambium samples (Ryan, 1982)
						DFBAR3	Presence (1) or absence (−1) of Douglas-fir beetle in years 1–3

Appendix C. Distributions of fire injury variables by region for live and dead trees

See Figs. C1–C12.

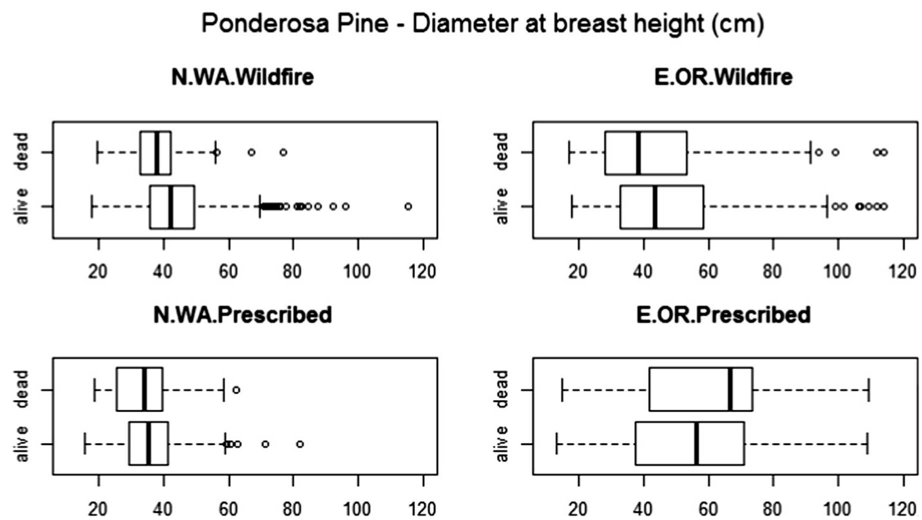

Fig. C1. Boxplots of diameter at breast height for ponderosa pine from wild or prescribed fire within geographic regions. N.WA is northern Washington state, E.OR is eastern Oregon.

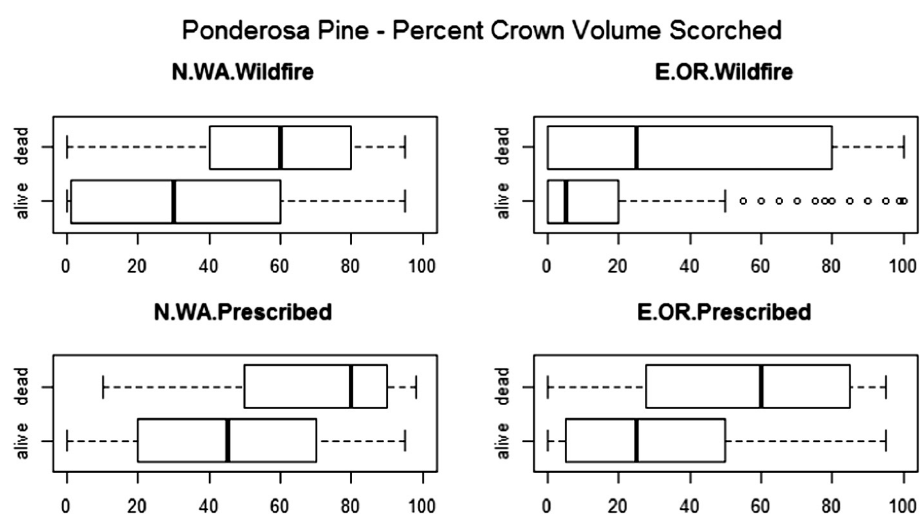

Fig. C2. Boxplots of percent of individual tree crown that was scorched in the fire for ponderosa pine from wild or prescribed fire within geographic regions. N.WA is northern Washington state, E.OR is eastern Oregon.

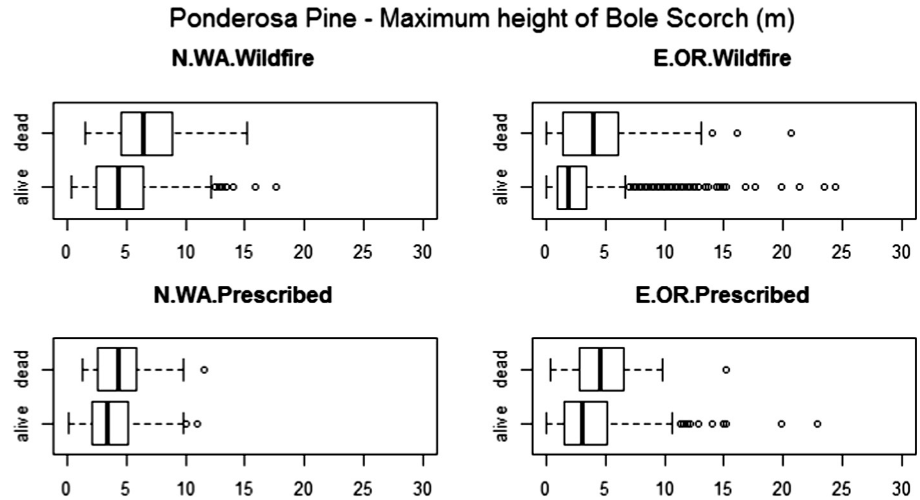

Fig. C3. Boxplots of percent of the maximum height of bole scorch as a proportion of tree height for ponderosa pine from wild or prescribed fire within geographic regions. N.WA is northern Washington state, E.OR is eastern Oregon.

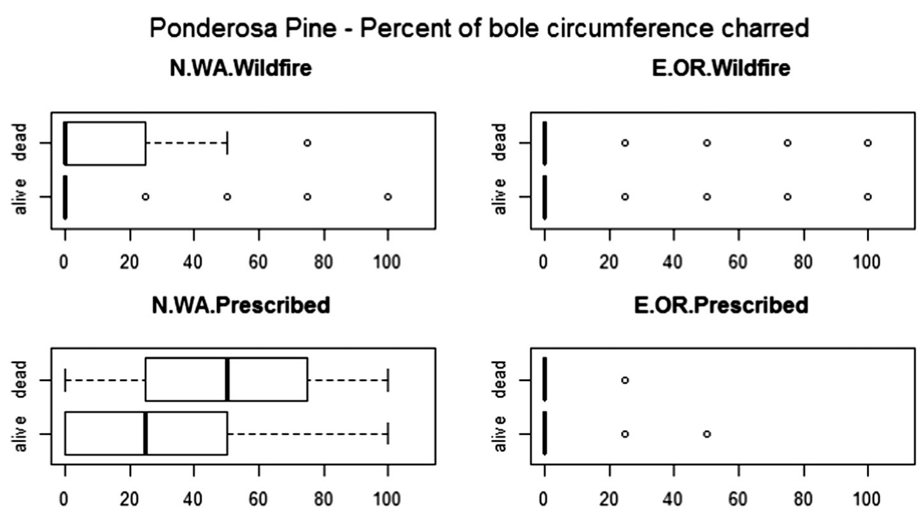

Fig. C4. Boxplots of the percent of the individual tree bole circumference that was charred in the fire for ponderosa pine from wild or prescribed fire within geographic regions. N.WA is northern Washington state, E.OR is eastern Oregon.

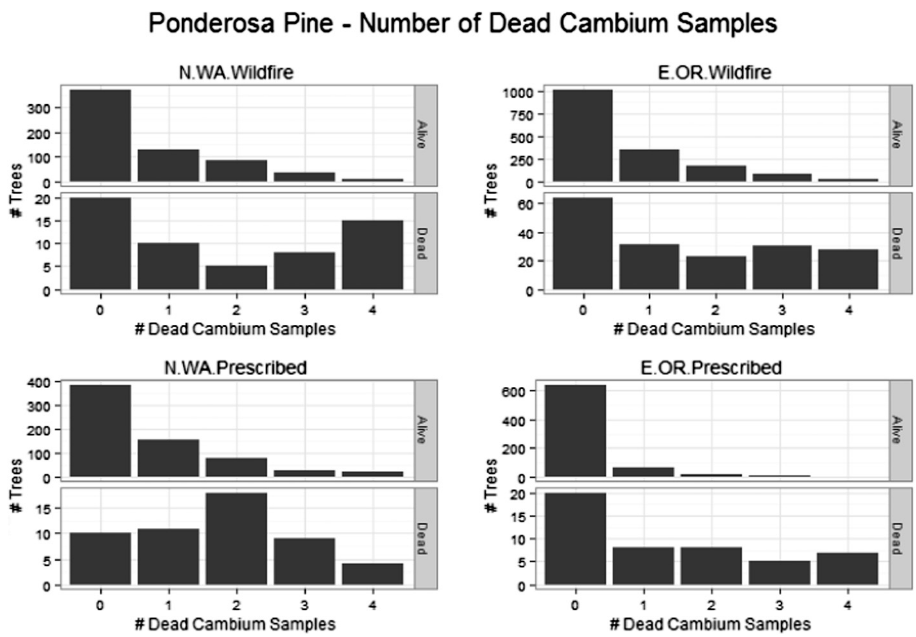

Fig. C5. Number of ponderosa pine trees with 0, 1, 2, 3, or 4 dead cambium samples from wild or prescribed fire within geographic regions. N.WA is northern Washington state, E.OR is eastern Oregon.

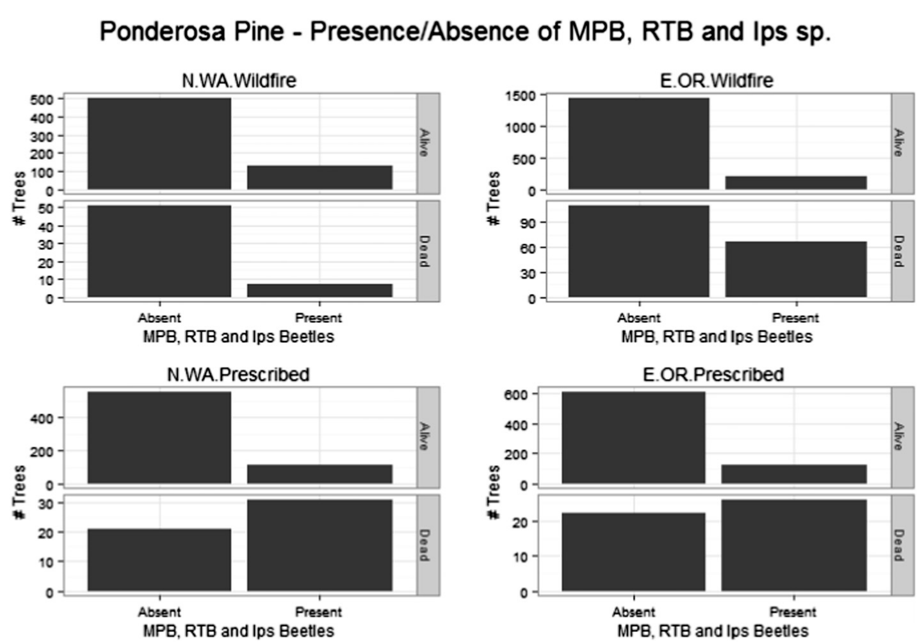

Fig. C6. Number of ponderosa pine trees with Mountain Pine beetle, Red Turpentine Beetle or Ips species present in 1–3 years post-fire from wild or prescribed fire within geographic regions. N.WA is northern Washington state, E.OR is eastern Oregon.

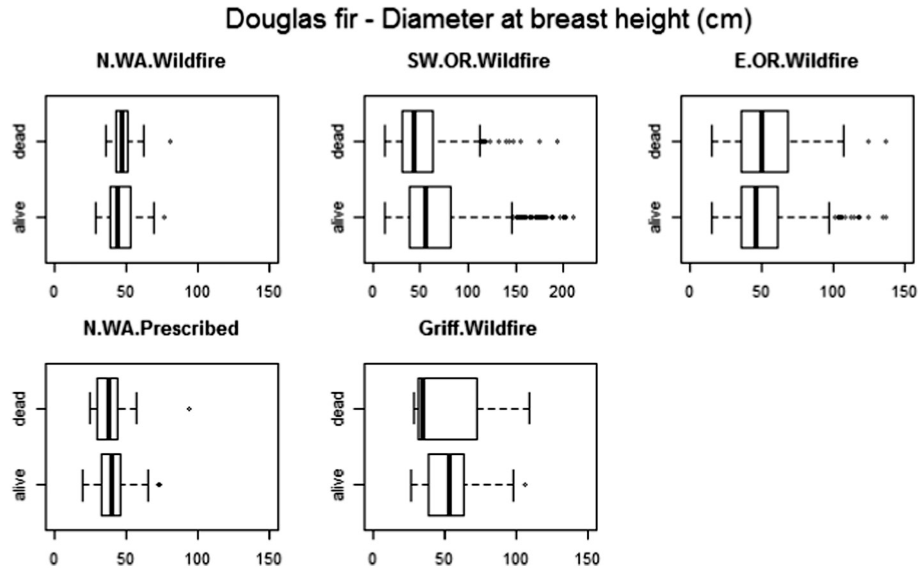

Fig. C7. Boxplots of diameter at breast height for Douglas-fir from m wild or prescribed fire within geographic regions. N.WA is northern Washington state, E.OR is eastern Oregon, SW.OR is southwestern Oregon and Griff is the Griff fire in northwestern Washington.

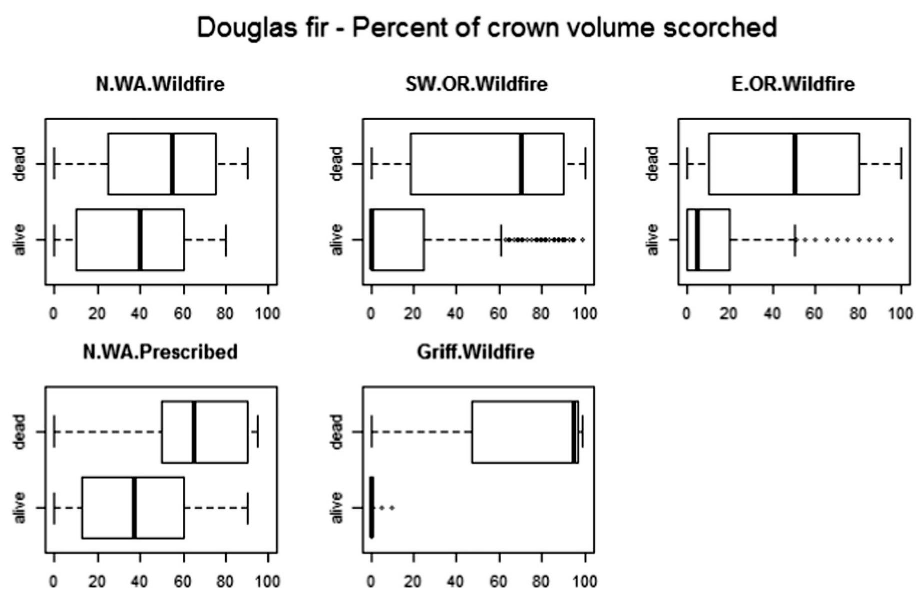

Fig. C8. Boxplots of percent of individual tree crown that was scorched in the fire for Douglas-fir from wild or prescribed fire within geographic regions. N.WA: northern Washington state, E.OR: eastern Oregon, SW.OR: southwestern Oregon, Griff: Griff fire in northwestern Washington.

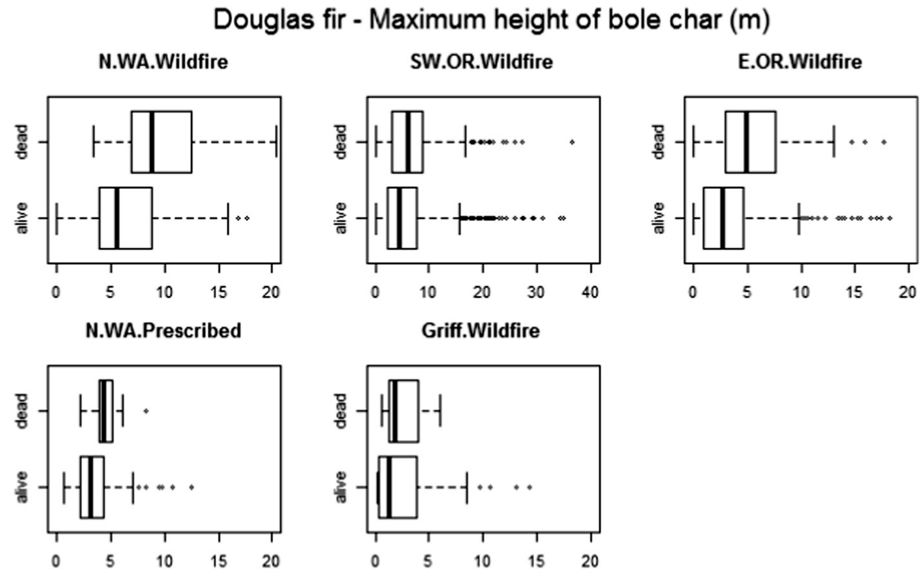

Fig. C9. Boxplots of percent of the maximum height of bole scorch as a proportion of tree height for Douglas-fir from wild or prescribed fire within geographic regions. N.WA is northern Washington state, E.OR is eastern Oregon.

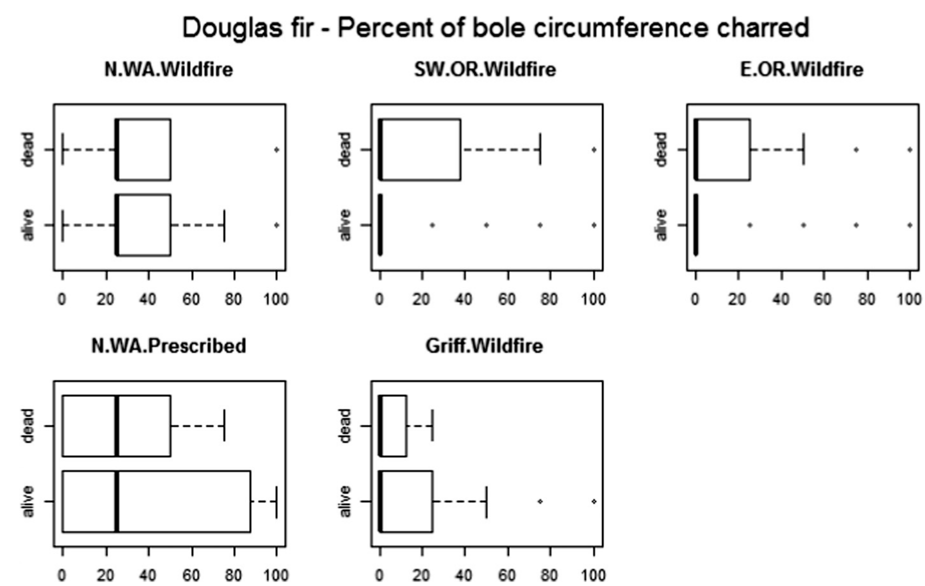

Fig. C10. Boxplots of the percent of the individual tree bole circumference that was charred in the fire for Douglas-fir from wild or prescribed fire within geographic regions. N.WA is northern Washington state, E.OR is eastern Oregon.

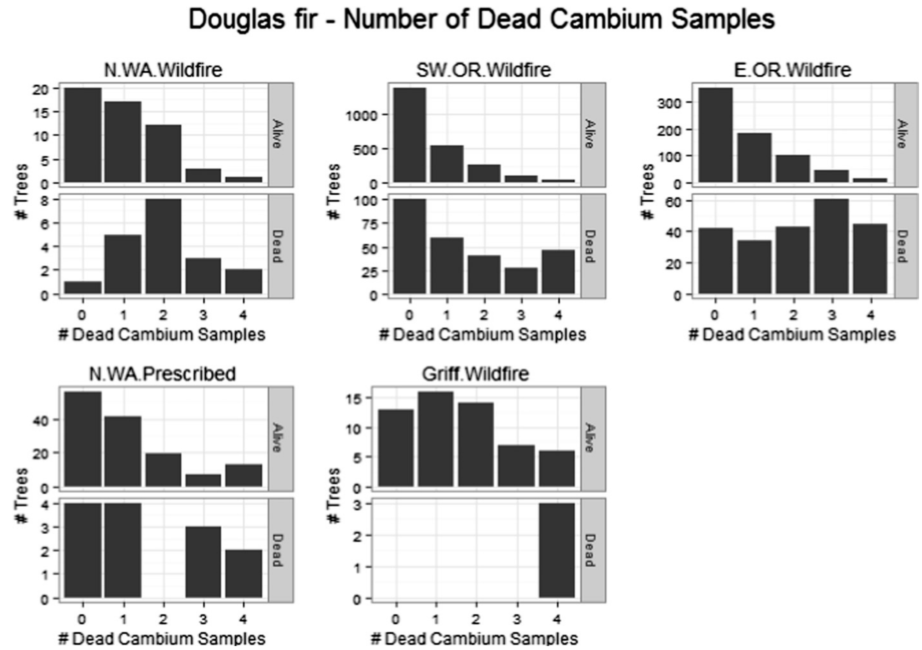

Fig. C11. Number of Douglas-fir trees with 0, 1, 2, 3, or 4 dead cambium samples from wild or prescribed fire within geographic regions. N.WA is northern Washington state, E.OR is eastern Oregon, SW.OR is southwestern Oregon and Griff is the Griff fire in northwestern Washington.

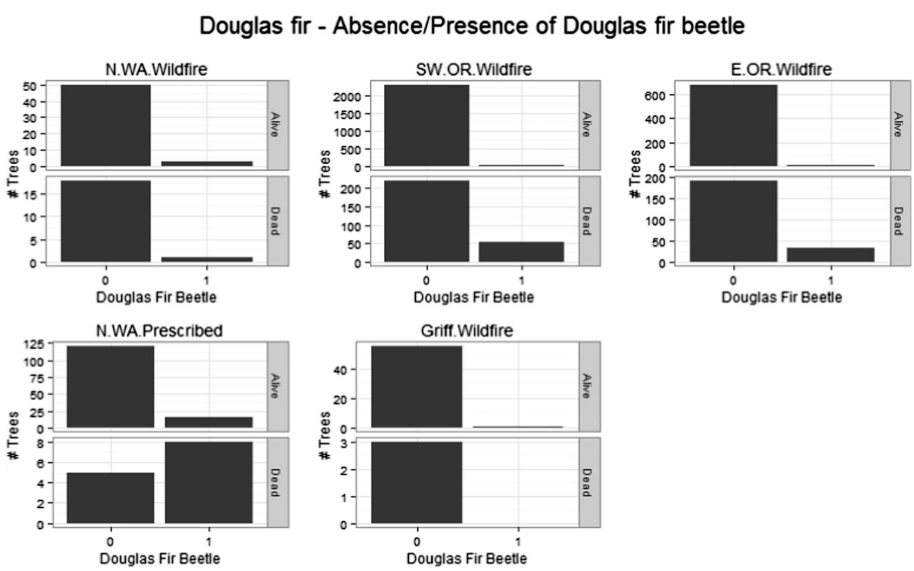

Fig. C12. Number of Douglas-fir trees with presence or absence of Douglas-fir beetle in 1–3 years post-fire from wild or prescribed fire within geographic regions. N.WA is northern Washington state, E.OR is eastern Oregon, SW.OR is southwestern Oregon and Griff is the Griff fire in northwestern Washington.

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