CHAPTER 9.

Monitoring Survival of Fire-Injured Trees in Oregon and Washington

(Project WC-F-08-03)

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INTRODUCTION

Wild and prescribed fire injury to trees can produce mortality that is not immediately apparent, and environmental stress subsequent to a fire may also contribute to tree mortality in the years after a fire (Hood and Bentz 2007). In order to predict post-fire tree mortality from fire injury variables before tree mortality is clearly apparent, dozens of statistical logistic regression models have been developed (see Woolley and others 2012 for a review), and some are incorporated within larger fire behavior and effects models and computer models used to support land management decisions (Hood and others 2007, Reinhardt and others 1997). In the Wallowa and Blue Mountains of northeastern Oregon, a polychotomous field key has been developed to predict tree mortality (Scott and others 2002). For this project, post-fire tree mortality and fire injury variables were collected for 26 wild and prescribed fires across Oregon and Washington, providing an opportunity to test specific published models for 16 species of conifers. Our objectives with these data are (1) to assess the ability of previously published logistic regression models and other guidelines or methods to predict 3-year post-fire tree mortality in Oregon and Washington State and (2) to identify suites of fire injury variables that best discriminate between live and dead trees in that region.

METHODS

Field Sampling

Twenty-six wild and prescribed fires that occurred between 1999 and 2009 and ranged over a wide geographical area from southwest Oregon to northeastern Washington were identified by local U.S. Department of Agriculture, Forest Service, Forest Health Protection offices in cooperation with Forest Service National Forest and District offices (table 9.1, fig. 9.1). Survival and a suite of fire injury metrics were monitored for approximately 13,000 trees representing 16 species that burned in fires in the Pacific Northwest. Tree species included Douglas-fir (*Pseudotsuga menziesii*), Pacific silver fir (*Abies amabilis)*, white fir (*A. concolor*), Grand fir (*A. grandis*), subalpine fir (*A. lasiocarpa*), incense cedar (*Calocedrus decurrens*), Port Orford cedar (*Chamaecyparis lawsoniana*), Alaska-cedar (*C. nootkatensis*), Western redcedar (*Thuja plicata*), Ponderosa pine (*Pinus ponderosa*), lodgepole pine (*P. contorta*), sugar pine (*P. lambertiana*), western white pine (*P. monticola*), Engelmann spruce (*Picea engelmannii*), Western larch (*Larix occidentalis*), and western hemlock (*Tsuga heterophylla*). Existing logistic models adequately described post-fire mortality of *A. concolor, A. lasiocarpa, C. decurrens, C. lawsoniana, L. occidentalis, P. engelmannii, P. contorta,* and *P. lambertiana.* Field crews selected trees for measurement if

Table 9.1—Fire name, year of fire, fire location (latitude, longitude), and average annual rainfall for the location of the fire

Fire	Year	Latitude, longitude	Average annual rainfall
			inches
Apple	2002	43.2763389, -122.5235750	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	44.9913944, -122.0388583	94.49
Bull Spring	2003	44.8367667, -118.9231056	21.65
Clark	2003	43.9882806, -122.5755944	59.06
Columbia Complex	2007	46.2700556, -117.7109472	33.86
Davis Lake	2003	43.5981028, -121.7084917	38.58
Egley	2007	43.7369389, -119.4225611	20.08
Fischer	2004	47.5804671, -120.5646950	24.80
Grapple	2007	44.0447111, -118.7549306	23.23
Griff	2003	48.0234694, -123.4155472	58.27
Herman Creek	2003	45.6503472, -121.9022778	101.57
Hud2	2005	48.3854722, -119.2580028	12.60
Monument	2007	45.2517500, -119.3753389	14.96
Nile	2004	46.8574822, -121.0049832	27.95
Pearrygin Creek	2005	48.5053843, -120.1336373	15.75
Quartz	2001	42.3622750, -122.1094167	51.97
Rancheria Creek	1999	42.5597889, -122.3755806	51.18
School	2005	42.3622750, -122.1094167	20.47
Shake Table	2007	42.5597889, -122.3755806	21.65
Sharps Ridge	2007	44.8611361, -118.9621972	24.80
Sisters	2006	46.27249585, -117.603965	14.57
Squaw Creek	2005	44.2963639, -119.2479639	22.44
Tiller Complex	2009	44.8611361, -118.9621972	50.79

any green needles were present on the tree and fire injury was present; the goal was to sample at least 500 trees in each fire. Fire severity variables were measured for models addressed in the current literature. Initial assessments of tree condition and fire injury variables were completed during the summer of the year of the fire or in the following spring after budbreak if the burn occurred early- to mid-summer, or during the following summer if the fire occurred in late summer or early fall. The variables that were collected were chosen so as to match, or to calculate, variables collected in previous studies of post-fire tree mortality.

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

- Tree species
- Diameter at breast height (d.b.h.) measured to the nearest 0.25 cm on the uphill side of the tree at 1.37 m above mineral soil
- Dwarf mistletoe rating recorded 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 percent (Ryan 1982)
- The distance from the ground to the following points on the tree recorded using an Impulse 200 Laser hypsometer (Laser Technologies, Englewood, CO) with measurements 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, assessed as dead or alive in each bole quadrant with bark removed to within 0.25 to 0.50 cm of the cambium and a bark punch drilled into the cambium, if necessary
- Bole scorch scored as 0, 1, 2, or 3 in each quadrant of the tree bole following methods in Ryan (1982)

After the initial assessment, every year, for up to 5 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. No bark was removed from living trees to determine the success of the beetle infestation to avoid injury that could have been detrimental to its survival. If the tree subsequently died, bark beetle galleries were examined to determine the species present.

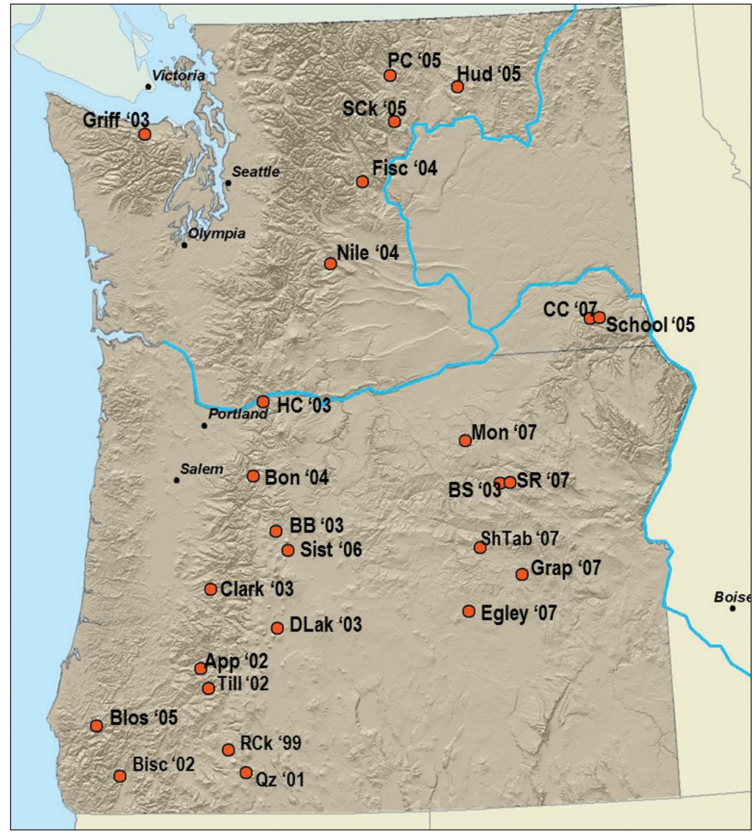

Figure 9.1—Location of 26 wild and prescribed fires that occurred in Washington and Oregon between 1999 and 2009 from which data were collected.

Data Analysis

In the process of building new models for our Oregon and Washington data, we selected suites of potential variables based on the examination of the distributions of the explanatory variables, the discriminatory ability of the previously published models, and our desire for a simple but broadly applicable model. We built new regression 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. In an effort to identify parsimonious models for our dataset, we also tested suites of variables with related but simpler terms. The Akaike information criterion (AIC) is a measure of the relative quality of statistical models for a given set of data. Given a collection of models for the data, AIC estimates the quality of each model, relative to each of the other models. Hence, AIC provides a means for model selection. In both approaches, we calculated the change in the AIC (Δ AIC) between the model in question and the model with the lowest AIC statistic as a measure of the support in the data for each model. Models with Δ AIC statistics between 0 and 2–7 are considered to be equally well supported by the data (Burnham and others 2011). To summarize the predictive ability of each model, we computed 95 percent confidence intervals for a tenfold cross-validated AUC (Area Under the Curve) statistic (James and others 2013) to reduce the bias that is known to occur when assessing predictive ability using data from which the model was built. All *P. ponderosa* and *P. menziesii* analyses were carried out using PROC GENMOD and PROC LOGISTIC in SAS® v. 9.4 (SAS Institute, Cary, NC, USA). Analyses of all other species were performed using R Studio® v. 3.3.1 (R Development Core Team).

Trees with probability of mortality (P_m) values higher than the chosen cutoff are predicted to die, and those with values lower than the cutoff are predicted to survive. A tree is classified as dead if the predicted probability of death from the regression model is greater than a predetermined decision criterion. For a chosen decision criterion, two types of misclassification errors can occur: dead trees predicted as live [false negative rate (FNR); trees predicted to live that died] or live trees predicted as dead [false positive rate (FPR); trees predicted to die that survived] (fig. 9.2). These two types of errors 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 live increases. That is, changing the decision criterion decreases one type of error but the other type must increase. Most studies report these accuracies using cutoff values at P_m of 0.5 or 0.6 (Ganio and Progar 2017; Grayson and others 2017; Hood and others 2007, 2010; Thies and others 2006). Typically, here, classification rates are estimated for a decision criterion of 0.5 where mistakenly predicting dead trees as live is minimized and mistakenly predicting live trees as dead is maximized. The decision criterion allows continuous P_m values to be converted to

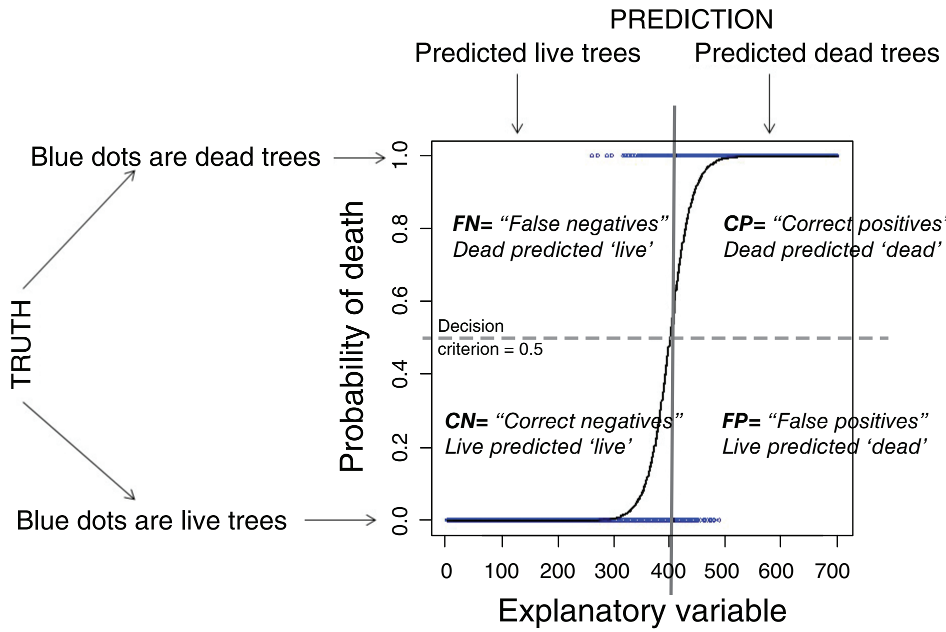

Figure 9.2—Graphical depiction of the probability of tree mortality modeled by logistic regression indicating how changing the decision criteria can affect type of error. Y-axis is the probability of death and the x-axis is the values of a measured explanatory value like crown or cambium kill. Increasing or decreasing the value of the decision criterion changes the decision of falsely predicting a dead tree will live or falsely predicting a live tree will die.

binary values in order to calculate true positive rate [(TPR); trees predicted to die and observed dead], true negative rate [(TNR); trees predicted to live and observed live], and the total percent of trees correctly classified (%C).

The Receiver Operating Characteristic (ROC) curve evaluates the specificity and sensitivity of the model over the range of decision criteria (0–1). In essence, AIC measures how well the model fits the data, while ROC describes how well the model predicts the outcome. Area under the ROC curve (AUC) is then taken as a measure of overall accuracy. When the units are normalized, the AUC is equivalent to the probability that the model will assign a higher score to a randomly chosen positive observation than to a negative one. That is, AUC is a measure of the chance that the model will predict a higher probability of mortality for a tree that was observed dead than to a tree that was observed live. We followed the rating system for AUC outlined by Hosmer and Lemeshow (2000). They report that ROC values equal to 0.5 suggest no discrimination from a 50-50 chance, values between 0.7 and 0.8 are acceptable discrimination (fair or adequate), values between 0.8 and 0.9 are excellent discrimination, and values > 0.9 are considered outstanding discrimination. Models with AUC values < 0.7 were considered poor, and those < 0.6 considered very poor.

RESULTS AND DISCUSSION

Validation of Previously Published Logistic Regression Models

In Ganio and Progar (2017), we assessed the discriminatory ability of 22 existing logistic regression models and a polychotomous key. We also built new models for each tree species, and identify fire injury variables that consistently produce accurate mortality predictions. The prediction of post-fire mortality of *P. menziesii* and *P. ponderosae* using previously developed models for specific fire types was not consistently better than prediction for all trees of each species regardless of the fire type (wild or prescribed burn). The overlap in 95 percent confidence intervals for AUC calculated from the subset and from all trees indicates similar average discriminatory ability. The distributions of fire injury variables for live and dead trees in our dataset are similar for both prescribed and wild fire and thus models will discriminate between live and dead trees to the same degree regardless of fire type. 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 *P. menziesii*, models that included these variables had average predictive ability above 80 percent, but, for ponderosa pine, average predictive ability is not above 80 percent, suggesting that it can be more difficult to identify dying ponderosa pine trees.

In Grayson and others (2017), we validated 54 logistic regression tree mortality models from seven published articles and two sets of mortality guidelines from two sources. We developed new logistic regression models for species with adequate sample size and which had no existing species-specific model (*A. amabilis, A. grandis, P. monticola,* and *T. heterophylla*). Most of our recommended models contained a crown scorch term and either a cambium injury term or a bark beetle infestation term. As many of these species have never been validated before, this paper provides users with previously unknown expected accuracy of mortality equations and identifies areas where additional data are needed. New thresholds of post-fire mortality were developed for *A. amabilis, A. concolor, A. grandis, P. contorta, P. lambertiana, P. monticola, P. engelmannii, L. occidentalis,* and *T. heterophylla.* We were not able to develop acceptable logistic mortality models or thresholds for *C. nootkatensis* or *T. plicata* because of small sample sizes. Injury to cambium and crown were both significant predictors in all but one set of new thresholds. The validation of existing models and guidelines allows managers to determine which models will likely perform best and identifies knowledge gaps where no adequate models exist to predict post-fire tree mortality. The new logistic regression models and threshold guidelines provide improved accuracy, with simpler application for fire and forest management.

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, when using a model to predict mortality, may wish to change the decision criterion for a particular application from the typical 0.5 to something higher to control the particular error that is most costly in their application.

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