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Predicting post-fire tree mortality for 14 conifers in the Pacific Northwest, USA: Model evaluation, development, and thresholds

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ABSTRACT

Fire is a driving force in the North American landscape and predicting post-fire tree mortality is vital to land management. Post-fire tree mortality can have substantial economic and social impacts, and natural resource managers need reliable predictive methods to anticipate potential mortality following fire events. Current fire mortality models are limited to a few species and regions, notably *Pinus ponderosa* and *Pseudotsuga menziesii* in the western United States. The efficacy of existing mortality models to predict fire-induced tree mortality is central to effective forest management. This study validated 54 logistic regression mortality models from seven published articles and two sets of mortality guidelines from two sources. Survival and a suite of fire injury metrics were monitored for 3654 trees representing 14 species that burned in fires between 2002 and 2009 in the Pacific Northwest, USA. Tree species included *Abies amabilis*, *A. concolor*, *A. grandis*, *A. lasiocarpa*, *Calocedrus decurrens*, *Chamaecyparis lawsoniana*, *C. nootkatensis*, *Thuja plicata*, *Pinus contorta*, *P. lambertiana*, *P. monticola*, *Picea engelmannii*, *Larix occidentalis*, and *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*. We also evaluated predictive accuracy of two published mortality guidelines that apply to species in the Pacific Northwest. In addition to validating existing models, we also developed new logistic regression models and simplified mortality guidelines, or thresholds. We created 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 recommended models contained a crown scorch term and either a cambium injury term or a bark beetle infestation term. New post-fire mortality thresholds 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 validate or develop acceptable logistic mortality models or thresholds for *C. nootkatensis* or *T. plicata*. 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.

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1. Introduction

Understanding post-fire tree mortality is essential, as wildland and prescribed fires burn millions of forested hectares annually (Bowman et al., 2009) and forests represent a major source of carbon storage, drive numerous ecosystem processes, and have economic and social importance (Allen et al., 2015; Anderegg et al., 2015). Land managers need to accurately predict tree mortality to plan prescribed burns and fuel treatments to meet mortality-related objectives. In addition, predictions of expected levels of tree mortality are important for planning post-fire management activities, such as salvage and reforestation.

The majority of post-fire tree mortality models are empirical and based on tree defenses (bark thickness) and fire injury (crown scorch, stem char) (Woolley et al., 2012). Crown injury is often the most important factor influencing post-fire tree mortality (Ryan, 1982b; Sieg et al., 2006) and is quantified by either percentage of crown length scorched or, more commonly, by percentage of crown volume scorched (Hood et al., 2010). Scorch height or char

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height, measured as total length or proportional to tree height, are also used as measures of crown injury (Sieg et al., 2006; Thies et al., 2006). These height variables relate to flame length, a measure of fireline intensity, but do not describe the actual amount of crown foliage or buds affected by fire. Cambium death caused by lethal heating of the tree bole is another influential factor in tree mortality following fire. Heat exposure to trees with thin bark or long-term smoldering of duff and large fuels around the base of trees with thick bark can kill cambial tissue (Ryan and Frandsen, 1991; Hood, 2010). Species-specific bark thickness equations as a function of tree diameter are most commonly used as a surrogate for probability of cambium death (Ryan and Reinhardt, 1988). There is a good relationship between bark char severity and cambium status for species with thin bark, but not for species with thick bark (Breece et al., 2008; Hood et al., 2008). Various methods have been used to quantify cambium kill, from direct sampling of the cambial tissue (Peterson and Arbaugh, 1989; Ryan and Frandsen, 1991; Hood and Bentz, 2007) to indirect measures such as amount or height of bark scorch or bark char severity (McHugh and Kolb, 2003; Thies et al., 2006).

Bark beetles can cause additional post-fire tree mortality by infesting and killing trees weakened by fire that likely would have survived otherwise (Hood and Bentz, 2007; Jenkins et al., 2014). Secondary beetles, such as red turpentine beetles (*Dendroctonus valens* LeConte) and ambrosia beetles (*Trypodendron* and *Gnathotrichus* spp.), are not typically considered "tree killers" (Hagle et al., 2003), but they may interact with post-fire tree injuries or primary bark beetles to cause additional mortality. For example, ambrosia beetles typically infest dead or dying trees, therefore these beetles can indicate fire-damaged tree is dying without contributing to its death (Hood et al., 2010).

Numerous post-fire tree mortality models have been developed, but model comparisons are challenging as their inputs vary widely, validation is limited, and most datasets have small sample sizes that cover small geographic areas (Woolley et al., 2012). Attempts at model validation have been nearly non-existent or restricted to a few species and geographic locations (but see Hood et al., 2007b; Ganio and Progar, 2017), making confidence in the general applicability of these models extremely limited. The mostly widely used post-fire mortality model (Ryan and Amman (1994) is employed in U.S. fire behavior and effects software programs such as the First-Order Fire Effects Model (FOFEM; Reinhardt et al., 1997), Fire and Fuels Extension to the Forest Vegetation Simulator (FFE-FVS; Reinhardt and Crookston, 2003), and BehavePlus (Reinhardt et al., 1997; Reinhardt and Crookston, 2003; Andrews, 2014). However, even it lacks strong empirical validation and is based on empirical data from just 7 species (Hood et al., 2010). Though the mortality models in FOFEM and other software programs were originally developed from these limited data in the Northern Rockies, USA, FOFEM is applied and used to predict post-fire mortality for 219 species throughout the USA, highlighting the need for model validation to other geographic regions and species. More than half of post-fire mortality studies and subsequent models developed in the western United States focus on Douglas-fir (*Pseudotsuga menziesii* (Mirbel) Franco) and ponderosa pine (*Pinus ponderosa* P. & C. Lawson) (Woolley et al., 2012). Further, many models were developed from data collected in relatively dry regions, such as the Rocky Mountains and the Sierra Nevada of California, in particular (Woolley et al., 2012). There is clearly a need to validate model accuracy for additional species and other regions.

Forests in the Pacific Northwest, USA, are diverse, productive, and increasingly fire-prone (Hessburg et al., 2015). Ponderosa pine and Douglas-fir mortality models are available for this region (Peterson and Arbaugh, 1989; Raymond and Peterson, 2005; Thies et al., 2006; Prichard and Kennedy, 2012; Ganio and Progar, 2017), but virtually no research on post-fire mortality for other species exists. Scott (2002) developed guidelines to predict post-fire individual tree mortality for several species in eastern Washington and Oregon based on available literature at the time. However, these guidelines have not been validated and require several steps to determine mortality risk, making interpretation complicated. We collected data from 13 fires in Washington and Oregon to assess the efficacy of previously published post-fire mortality models for 14 species in the Pacific Northwest. A companion paper presents similar results for ponderosa pine and Douglas-fir post-fire tree mortality (Ganio and Progar, 2017). We developed new models for those species for which current models are either inadequate or non-existent, and explored the feasibility of using simpler thresholds to predict mortality in lieu of logistic regression models. Our evaluations provide managers with clear guidance on model performance in the Pacific Northwest to aid in selecting models that best fit a particular land management need. Our validation exercise also extends the geographic relevance of several existing mortality models and highlights the need for additional validation of some models and where no adequate models exist for some species.

2. Methods

2.1. Field sampling

Sampling methods are detailed in Ganio and Progar (2017) and include the full dataset from all species and fires. Here, we present data only from fires where species other than ponderosa pine and Douglas-fir were assessed. Briefly, data was collected between 2002 and 2009 from 13 wildfires in Washington and Oregon (Fig. S1; Table S1). Species included *Abies amabilis* (Dougl. ex Loud.) Dougl. ex Forbes (ABAM; Pacific silver fir), *Abies concolor* (Gord. & Glend.) Lindl. Ex Hildebr. (ABCO; white fir), *Abies grandis* (Douglas ex D. Don) Lindl. (ABGR; grand fir), *Abies lasiocarpa* (Hook.) Nutt. (ABLA; subalpine fir), *Calocedrus decurrens* (Torr.) Florin (CADE; incense-cedar), *Chamaecyparis lawsoniana* (A. Murray bis) Parl. (CHLA; Port Orford cedar), *Chamaecyparis nootkatensis* (D. Don) Spach (CHNO; Alaska cedar), *Larix occidentalis* (Nutt.; LAOC; western larch), *Picea engelmannii* (Parry ex Engelm.; PIEN; Engelmann spruce), *Pinus contorta* (Dougl. var. *latifolia* Engelm.; PICO; lodgepole pine), *Pinus lambertiana* (Douglas; PILA; sugar pine), *Pinus monticola* (Douglas ex D. Don; PIMO3, western white pine), *Thuja plicata* (Donn ex D. Don; THPL; western redcedar), and *Tsuga heterophylla* (Raf.) Sarg. (TSHE; western hemlock). Species nomenclature follows the PLANTS Database (USDA; NRCS, 2017). To ensure that tree survival could be evaluated for 3 years post-fire, we sampled sites that burned as mixed-severity fires with a range of fire-injured, live trees and with no planned post-fire management activities.

Initial assessments of fire injury and tree condition were made within one year of the fire. The first growing season following the fire, we collected the following data on individual trees: species; status (live/dead); diameter at breast height (DBH; 1.4 m above ground); tree height (HT); pre-fire crown base height, assessed as the lowest living branch (Precrown); post-fire crown base height (Postcrown); beetle infestation (BTL; presence/absence by species, where possible); distance to large woody debris (DWM) (Scott, 2002); bole scorch height (BSH); crown volume scorch (CVS); bole char rating on each quadrant (Ryan, 1982a); cambium mortality on each quadrant (CKR) (Hood et al., 2007a); ground char rating on each quadrant (Ryan, 1982b); and dwarf mistletoe rating (Hawksworth, 1977). See Table 1 for the list and description of all attributes. Tree status (live/dead) and bark beetle infestations were reassessed each year for a minimum of three years and up to five years post-fire.

Table 1
Variable description and abbreviation. See text for additional details.

Variable code	Description
CVS	Percent crown volume scorched (100%, 50%, etc.). Includes crown kill and needle consumption
DBH	Diameter at breast height (cm)
BT	Bark thickness (cm; BT = bt * DBH; bt = bark thickness constant)
SH	Crown scorch height (m)
CH	Stem bark char height (m)
RCH	Relative char height (m; CH/Tree height)
PCLS	Percent crown length scorched (100%, 50%, etc.)
AB	Presence of ambrosia beetles (presence = 1, absence = -1)
RTB	Presence of red turpentine beetles (presence = 1, absence = -1)
CKR	Cambium kill rating (number of cambium quadrants killed)
BTL	Beetle presence/absence (presence = 1, absence = -1)
PBC	Percent ground level bole char
DMR	Dwarf mistletoe rating
Precrown	Pre-fire crown base fuel height (m)
CL	Crown length (m)
CLS	Crown length scorched (m)
BSH	Maximum bole scorch height (m)
ABS	Average bole scorch rating
AGC	Average ground char rating
CR	Crown ratio
IB	Initial beetle: Year 1 attack status (presence = 1, absence = 0)
Season	Season of fire ignition
SQ	Site quality, pre-fire vigor, and growth rate
DWM	Distance to large, downed woody material
RD	Root disease presence in true firs
BP	Relative distance to known infestation of pertinent beetles

2.2. Data analysis

Analyses were performed using R Studio v. 3.3.1 (R Development Core Team, 2016). Statistical significance was evaluated at $\alpha < 0.05$ unless otherwise stated. We created an additional code for bark beetles as presence or absence of primary beetles (PRI), which included *Dendroctonus ponderosae* (Hopkins) and *D. rufipennis* (Kirby). FOFEM v5 predicts post-fire mortality using crown volume scorched and a bark thickness value (BT) based on species and DBH. To validate the FOFEM v.5 equations we used the species-specific bark thickness constants from Reinhardt et al. (2009). Crown ratio (CR), crown length scorch (CLS), and percent crown length scorch (PCLS) were calculated using tree height, pre-fire crown base height, and post-fire crown base height. Most tree mortality typically occurs within three years post-fire (Hood et al., 2010; Ganio and Progar, 2017) and more trees in the dataset were followed for 3 years than for 5 years. Thus, we used 3-year post-fire mortality in both model validation and new model and guideline development. We calculated basic descriptive statistics by species and by species and status for DBH, CVS, and CKR, and evaluated differences in means between live and dead trees with nonparametric Wilcoxon rank-sum tests.

2.3. Model validation

There is no single approach to assess the efficacy of a logistic regression, and several different methods exist that may or may not be helpful depending on management objectives. Data were not collected at the stand level, so we only considered individual tree metrics. Contingency tables that evaluate hit rates are common, but accuracy varies by the decision criterion (or cutoff) chosen. 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. The decision criterion allows continuous P_m values to be converted to 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), false positive rate (FPR; trees predicted to die which survived), false negative rate (FNR; trees predicted to live which died), and the total percent of trees correctly classified (% C). Most studies report these accuracies using cutoff values at P_m of 0.5 or 0.6 (Thies et al., 2006; Hood et al., 2007b, 2010; Ganio and Progar, 2017). All hit rates are reported at $P_m = 0.5$ unless otherwise noted.

Other common methods of assessing model efficacy are Akaike's information criterion (AIC) and the receiver operating characteristic (ROC) curve. AIC assesses a model's goodness of fit to a particular dataset and penalizes for increasing model complexity. It represents a balance in the distance between values predicted by the model and values observed in the dataset and how many terms and observations are required for the model. AIC is generally used in model development to select the best performing model within a species. ROC 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 alive. 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 greater than 0.9 are considered outstanding discrimination. Models with AUC values below 0.7 were considered poor, and those below 0.6 considered very poor.

We validated all published post-fire mortality logistic regression models for which we had the required inputs available for the species in our dataset (Tables 2 and S2). Seven species had only the FOFEM 5 model available for validation which uses crown volume scorched and a species-specific bark thickness equations; for those, we also tested how other models from similar species performed. For example, the only available model for grand fir was the FOFEM 5 model. We thus examined the ability of the white fir models to predict the post-fire mortality of the grand fir data. We evaluated model accuracy using the 0.25, 0.5, 0.75, and 0.9 decision criteria and also report the total correct and AUC (Robin et al., 2011).

In addition to the available logistic regression models, we evaluated two other guidelines developed to predict post-fire mortality in the Pacific Northwest. Scott (2002) developed a rating system for several conifer species in the Blue and Wallowa Mountains of Oregon. In Scott's guidelines, each tree is assessed a score based on a series of factors, including season of fire, site quality, fuel load, and disease. Species-specific factors include age class, size class, crown scorch, bole scorch (i.e., char), and duff consumption. The final score is used to classify predicted mortality as low, moderate, or high (decision classes vary for each tree category and assumes that 50% of the trees classified as moderate will die). We evaluated the guidelines, as written, into low, moderate, and high probability of survival, as well as into a predicted dead or live category. This was done by splitting the score for the moderate survival probability in half. Those with a score higher than the middle score for moderate survival were considered to be predicted to live, and those with a score less than the middle value were considered to be predicted to die (Scott, 2002); this allowed for a direct comparison to observed data. We validated the Scott guidelines (Scott, 2002; Scott et al., 2003) for white fir, grand fir, subalpine fir, western larch, lodgepole pine, Engelmann spruce, and western white

Table 2
Source, species, and validation method of tree mortality equations assessed. For FOFEM v5 models, equation abbreviation is the four letter species code followed by the numeral 1 (e.g. ABCO 1, CADE 1, etc.). Full species names are listed in Table S3 and variable description in Table 1.

Species code	Equation abbreviation	Source	Variables
All	SPEC 1	FOFEM v5 Ryan and Amman (1994)	DBH, CVS
Firs			
ABCO	ABCO 2	Mutch and Parsons (1998)	DBH, CVS
ABCO	ABCO 3	Stephens and Finney (2002)	DBH, CVS
ABCO	ABCO 4	Hood et al. (2010)	DBH, PCLS, CKR, AB
ABCO	ABCO 5	Hood et al. (2010)	DBH, PCLS, AB
ABCO	ABCO 6	Hood et al. (2010)	DBH, PCLS, CKR
ABCO	ABCO 7	Hood et al. (2010)	DBH, PCLS
ABCO	ABCO 8	Hood et al. (2010)	PCLS
ABCO	ABCO 9	Hood and Lutes (2017)	PCLS
ABCO	ABCO 10	Hood and Lutes (2017)	DBH, PCLS, CKR, BTL
ABCO	ABCO S	Scott (2002), Scott et al. (2003)	Season, SQ, DWM, DMR, RD, BP, CVS, ABS, SH, AGC
ABCO	ABCO W	Wagener (1961)	CVS, CKR
ABGR	ABGR S	Scott (2002), Scott et al. (2003)	Season, SQ, DWM, DMR, RD, BP, CVS, ABS, SH, AGC
ABLA	ABLA 2	Hood and Lutes (2017)	CVS
ABLA	ABLA 3	Hood and Lutes (2017)	CVS, CKR
ABLA	ABLA S	Scott (2002)	Season, SQ, DWM, DMR, RD, BP, CVS, ABS, SH, AGC
"Cedars"			
CADE	CADE 2	Stephens and Finney (2002)	DBH, CVS
CADE	CADE 3	Stephens and Finney (2002)	DBH, SH
CADE	CADE 4	Regelbrugge and Conard (1993)	DBH, CH
CADE	CADE 5	Regelbrugge and Conard (1993)	DBH, CH
CADE	CADE 6	Regelbrugge and Conard (1993)	RCH
CADE	CADE 7	Regelbrugge and Conard (1993)	RCH
CADE	CADE 8	Hood et al. (2010)	CVS, CKR
CADE	CADE 9	Hood et al. (2010)	CVS
CADE	CADE 10	Hood et al. (2010)	PCLS, CKR
CADE	CADE 11	Hood et al. (2010)	CVS
CADE	CADE 12	Hood and Lutes (2017)	PCLS
CADE	CADE 13	Hood and Lutes (2017)	PCLS, CKR
CADE	CADE W	Wagener (1961)	CVS, CKR
Pines			
PICO	PICO 2	Hood and Lutes (2017)	CVS, DBH
PICO	PICO 3	Hood and Lutes (2017)	DBH, CVS, CKR
PICO	PICO S	Scott (2002), Scott et al. (2003)	Season, SQ, DWM, DMR, RD, BP, CVS, ABS, SH, AGC
PILA	PILA 2	Mutch and Parsons (1998)	CVS
PILA	PILA 3	Stephens and Finney (2002)	CVS
PILA	PILA 4	Stephens and Finney (2002)	DBH, SH
PILA	PILA 5	Hood et al. (2010)	PCLS, CKR, RTB
PILA	PILA 6	Hood et al. (2010)	PCLS, RTB
PILA	PILA 7	Hood et al. (2010)	PCLS, CKR
PILA	PILA 8	Hood et al. (2010)	PCLS
PILA	PILA 9	Hood and Lutes (2017)	PCLS
PILA	PILA 10	Hood and Lutes (2017)	PCLS, CKR, BTL
PILA	PILA 11	Nesmith et al. (2015)	DBH, CVS, PBC
PILA	PILA 12	Nesmith et al. (2015)	DBH, CVS
PILA	PILA W	Wagener (1961)	CVS, CKR
PIMO	PIMO S	Scott (2002)	Season, SQ, DWM, DMR, RD, BP, CVS, ABS, SH, AGC, DBH
Spruce			
PIEN	PIEN 2	Hood and Lutes (2017)	CVS
PIEN	PIEN 3	Hood and Lutes (2017)	CVS, CKR
PIEN	PIEN S	Scott (2002)	Season, SQ, DWM, DMR, RD, BP, CVS, ABS, SH, AGC
Larch			
LAOC	LAOC 2	Hood and Lutes (2017)	DBH, CVS
LAOC	LAOC 3	Hood and Lutes (2017)	CVS, CKR
LAOC	LAOC S	Scott (2002)	Season, SQ, DWM, DMR, RD, BP, CVS, ABS, SH, AGC

pine. Beetle pressure (i.e., relative distance of host species tree to the nearest known infestation) was evaluated by the presence of primary beetles noted on any tree in the area (presence = 3, absence = 1, non-host = 0). We did not use the intermediate distance range for bark beetle pressure in the guidelines, as we lacked more detailed data of bark beetle populations and locations. We assessed the "pre-fire vigor, growth rate, and site quality" factor by assigning a value of 1 to trees with both a crown ratio value <0.4 and local basal area $\geq$23 m^2/ha (Donald Scott, personal communication) and a value of 0 to trees that did not meet both of these criteria. Ground char rating was evaluated in four quadrants per tree as described in Ryan and Noste (1985), where unburned = 0, light = 1, moderate = 2, and heavy/deep = 3. Ratings were averaged into one tree-level value and assigned the most closely matching description of the duff consumption factor in the Scott guidelines.

Wagener (1961) developed criteria for predicting post-fire mortality in California on 12 national forests and Yosemite National Park using fire period (i.e., season), cambium injury, live crown, and percent green foliage. Wagener's criteria also include optional adjustments due to "influencing factors" such as low quality sites, poor growth vigor, or fire season. We did not account for the optional adjustments, as we did not t have data for site quality or growth vigor and in preliminary analysis, fire season did not affect the decision criteria. We validated the Wagener criteria for white fir, sugar pine, and incense-cedar.

2.4. New logistic regression models

We developed new, species-specific and grouped-species logistic models through purposeful selection when either no other species-specific models had been developed or model validation showed poor predictive capacity of the data (Hosmer and Lemeshow, 2000; Bursac et al., 2008). We tested for polynomial relationship between crown damage and mortality by creating square and cubic terms of CVS and PCLS and a square term for CKR. We began with all variables available in the dataset where the full range of data was well described: DMR, BTL, DBH, Pre-crown, CL, CLS, PCLS, $PCLS^2$, $PCLS^3$, BSH, CVS, CVS^2, CVS^3, ABS, CKR, CKR^2, AGC, RCH, and CR (Table 1). The range of data has a major influence on modeling, making it unlikely that variables with limited ranges can be appropriately used to predict mortality. For instance, if the data of a particular species only includes CVS values from 0 to 30%, we cannot extrapolate to values higher than 30%. Variables were first checked for univariate significance to year 3 mortality via chi-square test for categorical variables and via logistic regression for continuous variables using a significance level of $p < 0.25$. We then checked for univariate significance with all possible 2-factor interaction terms using the same method.

We utilized distance correlation to check for multicollinearity among the remaining variables (Székely et al., 2007; Székely and Rizzo, 2016). We used logical associations along with a cutoff of correlation coefficient < ±0.3, a widely accepted mid-range value for weak correlation, to assess whether two variables were related. A major advantage of distance correlation to other correlation methods is that a zero correlation here implies data independence; therefore, only independent variables were used in model development. We then developed logistic regression models of the form:

$$P_m = 1/[1 + \exp(-(\beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k))]$$

using the variables identified in the univariate analysis. A subsequent forward selection procedure removed variables that were not significant in the multivariate model. Any variables that did not significantly affect the AIC (ΔAIC < 7; Burnham et al., 2011) were removed, except for cases when removing a term changed parameter estimates by $\geq$15%. This extra step allows for the inclusion of unexpected covariates and confounding variables. After final variable selection, we estimated coefficients using a 1000-replicate bootstrap with 20% random sample replacement (Canty and Ripley, 2016). The difference between the median bootstrap value and the bootstrap bias was used to estimate final coefficients. We sequentially dropped variables from the full model that are more difficult to predict before a fire (CKR and BTL) in order to examine variable importance and weigh complexity against accuracy.

We used AUC as the primary selection criterion for each model. Those that were similar in predictive accuracy were then ranked by AIC. This rule selects the model which best balances goodness of fit and model complexity. AIC was also used to determine if two models were equivalent in predictive accuracy, particularly where one model was more complex than the other. Models with a difference in AIC of less than 7 were considered equally supported by the data (Burnham et al., 2011). To aid in comparing many equations at once, we created a heatmap of each species and its equations for TPR, TNR, and %C over a range of values, as well as AUC. Because of the nature of a heatmap, AIC had to be normalized to a 0–1 scale, AICPts, where:

$$\text{AICPts} = \frac{(AIC - \min(AIC))}{\max(\text{AIC}) - \min(AIC)}$$

min (AIC) is the minimum AIC for any model for each species and max (AIC) is the maximum AIC for each species.

2.5. Developing threshold analyses

We explored the feasibility of using thresholds of post-fire mortality through a combination of piecewise regression and visual analyses of binned data using the same data used to develop new logistic regression models, except BTL. Since marking for silvicultural activities is typically done within a year post-fire, we used year 1 post-fire beetle infestation status (initial beetle, IB) rather than BTL. Thresholds can be easier to apply than logistic regression models, often without loss in accuracy (Fowler et al., 2010). We used histograms of the binned data to display the percent of trees across the range of values. This ensured that threshold values were clear points at which the behavior of the relationship between mortality and the variable changed. After a target range was selected by examining mortality response curves of the binned data, a univariate logistic regression was run at each value in that range. The value which yielded the model with the lowest residual deviance was used as the initial breakpoint estimate. This value and those near it were then evaluated to determine which breakpoint most successfully predicted mortality. Because of the uncertainty in evaluating crown volume scorch visually, CVS thresholds were selected so that a ±5% difference would not substantially affect the mortality prediction. In those guidelines that include a choice of two thresholds, both should be considered when predicting survival. That is to say, if the guidelines are CVS $\geq$ 50% or CKR $\geq$ 2, either may indicate mortality. However, it must fall below *both* criteria to indicate survival (e.g., a tree with 40% CVS and CKR = 3 will die, but a tree with 40% CVS and 2 CKR will survive).

3. Results and discussion

Every tree species except Alaska cedar exhibited a full range of CVS and CKR (Tables 3 and S3, Figs. S2–4). In general, minimum tree size was 12.7–18 cm DBH (Table S3). Incense-cedar had the lowest ratio of dead to live trees with only 4 dead trees and 50 live trees (Table 3). Western larch and Port Orford cedar displayed roughly 15% mortality. All other species had 25–55% tree mortality. Only Pacific silver fir, western larch, western redcedar, and western hemlock showed a significant difference in DBH between live and dead trees. Crown volume scorch was significantly different between live and dead trees for all species except subalpine fir, incense cedar, Port Orford cedar, Engelmann spruce, and western redcedar. Cambium kill rating was significant for all species except incense cedar, sugar pine, and western redcedar.

We report model validation results below for each species, arranged by general species groupings, and followed by newly developed models and thresholds. We developed new logistic regression for Pacific silver fir, grand fir, western white pine, and western hemlock. We lacked sufficient data to evaluate thresholds for incense cedar, Port Orford cedar, Alaska cedar, and western redcedar, but report new thresholds for post-fire mortality for all other species sampled.

3.1. Firs

3.1.1. Pacific silver fir

Pacific silver fir were monitored at four fires on four national forests for a total of 111 trees (Tables S1 and S3). Although CVS and CKR were higher for dead trees compared to live trees, and DBH was lower (Table 3), there was still considerable overlap in

Table 3
Range, median, mean, and standard error (SE) of crown volume scorch percent (CVS), diameter at breast height (DBH), and cambium kill rating (CKR) by species. Wilcoxon rank-sum test p-values compare dead and live trees by variable; asterisks indicate significance: * = p-value < 0.1, ** = p-value < 0.01, *** = p-value < 0.001. N = sample size. Percent of live and dead trees attacked by primary bark beetles, ambrosia beetles (AMB), and red turpentine beetles (RTB). Primary bark beetles include mountain pine beetle for all pine species; and spruce beetle for Engelmann spruce. Full species names are listed in Table S3.

Tree species	N Live N Dead	DBH (cm)			CVS (%)			CKR			Bark Beetle Attack		
		Median	Range	Mean (SE)	Median	Range	Mean (SE)	Median	Range	Mean (SE)	% Primary	% RTB	% AMB
Firs													
ABAM	47	57.7	17.5–113	58.7 (4.1)***	0	0–40	7 (1.7)***	3	0–4	2.6 (0.2)***	NA	NA	13
	64	47.5	18.5–111.8	52.3 (3)	0.5	0–95	12.4 (2.8)	4	0–4	3.5 (0.1)	NA	NA	14
ABCO	524	50.8	17.3–129.5	54.2 (0.9)	10	0–95	21.4 (1.1)*	1	0–4	1.2 (0.1)***	NA	0	25
	396	41.1	12.7–218.4	45.7 (1)	50	0–100	49.5 (1.6)	3	0–4	2.9 (0.1)	NA	0	40
ABGR	369	45.7	15.2–109.2	48.6 (1.1)	5	0–90	17.1 (1.2)***	1	0–4	1.2 (0.1)***	NA	NA	34
	381	43.2	15.2–106.7	47.8 (1)	37.5	0–100	41.6 (1.8)	3	0–4	2.5 (0.1)	NA	NA	48
ABLA	12	31.8	22.9–99.1	40.4 (6)	10	0–95	26.3 (9.4)	0.5	0–2	0.7 (0.2)***	NA	NA	50
	21	30.5	17.8–83.8	34.2 (3.3)	25	0–95	37.9 (7.8)	3	0–4	2.7 (0.3)	NA	NA	33
"Cedars"													
CADE	50	53.3	14.5–149.9	60.3 (4.5)	0	0–80	14.2 (3)	1	0–4	1.5 (0.2)	NA	NA	0
	4	29.2	22.4–86.6	41.8 (15.2)	53	0–92	49.5 (24.2)	0.5	0–4	1.3 (0.9)	NA	NA	25
CHLA	58	61	14–152.4	59.9 (3.8)	0	0–90	9.9 (2.4)	2	0–4	2.3 (0.2)**	NA	NA	3
	11	40.6	12.7–104.1	56.6 (10.2)	22	0–98	40.9 (12.3)	4	3–4	3.7 (0.1)	NA	NA	0
CHNO	13	31	20.3–62.2	32.4 (3.1)	0	0–20	2.8 (1.6)***	3	0–4	2.8 (0.3)***	NA	NA	0
	13	25.7	18.5–48.8	28.9 (2.3)	0	0–5	0.6 (0.4)	4	3–4	3.8 (0.1)	NA	NA	8
THPL	20	61.3	25.7–96.8	61.9 (3.8)*	1	0–88	6.6 (4.4)	3	1–4	2.8 (0.2)	NA	NA	5
	18	43.2	12.7–104.1	48.1 (6.9)	34	0–99	42.5 (9.4)	3.5	0–4	3.1 (0.3)	NA	NA	6
Pines													
PICO	41	24.1	14–50	28.2 (1.5)	0	0–50	8.2 (2.3)***	2	0–4	1.7 (0.2)***	15	10	5
	89	29.5	13.5–56.6	29.9 (1)	5	0–95	19.3 (2.8)	4	0–4	3.2 (0.1)	49	8	6
PILA	144	71.1	17.8–179.6	75.5 (2.7)	11	0–95	21.7 (2)***	1	0–4	1.3 (0.1)	2	20	1
	62	67.4	15.2–163.1	71.8 (4.6)	47.5	0–100	49.4 (4)	2	0–4	1.6 (0.2)	50	53	21
PIMO	46	35.4	17.8–74.7	39.8 (2.3)	7.5	0–90	18.7 (3.6)**	3	0–4	2.4 (0.2)***	3	17	0
	43	38.4	15.2–82	42 (2.7)	50	0–97	51.9 (4.4)	4	1–4	3.5 (0.1)	10	23	0
Spruce													
PIEN	58	45.6	17.8–94	46.4 (2)	0	0–75	9.2 (2.2)	2	0–4	1.6 (0.2)***	17	5	9
	153	46.7	13.5–91.4	47.1 (1.3)	10	0–100	26.2 (2.7)	4	0–4	3.4 (0.1)	5	1	17
Larch													
LAOC	377	35.6	14–111.3	38.6 (0.8)***	0	0–100	13.8 (1.3)***	1	0–4	0.9 (0.1)***	NA	1	7
	72	25.3	14.2–119.4	30.6 (1.9)	40	0–100	45.3 (4.8)	3	0–4	2.7 (0.2)	NA	0	14
Hemlock													
TSHE	198	47.6	14–112	50.7 (1.5)***	0	0–96	11.1 (1.6)***	3	0–4	3 (0.1)***	NA	NA	23
	370	40.6	12.7–132.1	46.3 (1.1)	30	0–99	38.9 (1.9)	4	0–4	3.8 (0)	NA	NA	50

range for all variables (Figs. S2–S4). No species-specific model exists for Pacific silver fir. We evaluated the predictive accuracy of FOFEM 5 and of existing white fir equations to the Pacific silver fir data (Table S2). None of these models performed exceptionally well, with a maximum AUC of just 0.71 and most total correctly classified (%C) values below 50% (Figs. 1 and 2). The FOFEM 5 model consistently predicted survival well (i.e., very high TNR), but mortality poorly (i.e., very low TPR), across all cutoffs (Fig. 1). Results were similar when white fir models were used, showing that these models do not predict Pacific silver fir mortality accurately (Fig. 2).

We developed two new mortality equations for Pacific silver fir:

$$\text{ABAM 2}: P_m = 1/(1 + e^{(-(-2.1403 + 0.8810*\text{ABS} + 0.09568*\text{CKR}^2))})$$

$$\text{ABAM 3}: P_m = 1/(1 + e^{(-(-1.7106 + 1.2949*\text{ABS}))})$$

The full model, ABAM 2, included ABS and CKR (AUC = 0.76; Fig. 1). Dropping CKR from the model resulted in only a minor loss (ABAM 3; AUC = 0.74) in accuracy (Fig. 1). We recommend that the uncertainty in these models be considered when using them, and that new models with more empirical backing should be developed.

The Pacific silver fir threshold model performed better than any of the logistic models (Table 5). Using a CKR = 4 as the predictor of mortality yielded correct classification 71% of the time. TPR were much improved from the logistic models, but the FPR was still rather high at 28%.

3.1.2. White fir

White fir were measured at seven fires on four national forests for a total of 920 trees (Tables S1 and S3). CVS tended to be higher for dead trees (Table 3, Fig. S4). Tree status by CKR showed a clear distinction with the majority of dead trees having CKR ≥ 2 (Table 3, Fig. S4). DBH did not differ between surviving and dead trees (Table 3, Fig. S2). Ten models exist for white fir (Table S2). Most of these performed at least moderately well, though all models except ABCO 2 and ABCO 3 underpredicted mortality at all P_m decision criteria (Fig. 1). The more complex models, ABCO 4, ABCO 6, and ABCO 10, with CKR and a beetle infestation (*Scolytus ventralis*, LeConte), variable in addition to DBH and crown scorch were most accurate. ABCO 10 had the highest accuracy, with an AUC of 0.81. However, simpler models with only PCLS or CVS and DBH (ABCO 1, ABCO 3, ABCO 8, and ABCO 9) still had AUC values $\geq$0.75, indicating crown scorch is the most important factor in predicting post-fire white fir mortality.

Both Wagener's criteria and the Scott guidelines include white fir (Table 4). The Scott guidelines performed poorly and overpredicted mortality, with a %C of 47% and a 92% FPR. Wagener's crite-

Model	TPR.1	TNR.1	Correct.1	TPR.25	TNR.25	Correct.25	TPR.5	TNR.5	Correct.5	TPR.75	TNR.75	Correct.75	TPR.9	TNR.9	Correct.9	AUC	AICPts
ABAM 1	0.66	0.51	0.59	0.33	0.68	0.48	0.11	0.94	0.46	0.06	1	0.46	0.05	1	0.45	0.57	0
ABAM 2*	1	0	0.58	0.95	0.21	0.64	0.81	0.45	0.66	0.44	0.91	0.64	0	1	0.42	0.76	1
ABAM 3	1	0	0.58	0.98	0.13	0.62	0.75	0.51	0.65	0.34	0.91	0.59	0	1	0.42	0.74	0
ABCO 1	0.97	0.2	0.53	0.78	0.52	0.63	0.5	0.86	0.71	0.39	0.94	0.7	0.26	0.98	0.67	0.77	0.36
ABCO 2	0.17	0.97	0.63	0.09	0.99	0.6	0.02	1	0.58	0	1	0.57	0	1	0.57	0.72	0.99
ABCO 3	0.4	0.93	0.7	0.31	0.96	0.68	0.23	0.98	0.66	0.11	1	0.61	0.03	1	0.58	0.78	0
ABCO 4	0.93	0.35	0.6	0.68	0.75	0.72	0.4	0.93	0.7	0.21	0.99	0.65	0.13	1	0.62	0.79	1
ABCO 5	0.91	0.17	0.49	0.65	0.68	0.67	0.36	0.92	0.68	0.2	0.98	0.65	0.12	1	0.62	0.7	0.95
ABCO 6	0.92	0.35	0.59	0.53	0.88	0.73	0.3	0.97	0.68	0.17	0.99	0.64	0.12	1	0.62	0.8	0.96
ABCO 7	0.93	0.1	0.46	0.45	0.85	0.68	0.28	0.96	0.67	0.16	1	0.64	0.11	1	0.61	0.66	0.92
ABCO 8	1	0	0.43	0.49	0.85	0.7	0.31	0.96	0.68	0.17	0.99	0.64	0.12	1	0.62	0.75	0.92
ABCO 9	0.77	0.54	0.64	0.45	0.87	0.69	0.27	0.98	0.67	0.15	1	0.63	0.11	1	0.61	0.75	0.9
ABCO 10*	0.96	0.29	0.58	0.7	0.76	0.73	0.38	0.94	0.7	0.21	0.98	0.65	0.13	1	0.62	0.81	1
ABGR 1	0.89	0.21	0.55	0.65	0.54	0.59	0.41	0.85	0.62	0.28	0.94	0.61	0.19	0.98	0.58	0.68	0.98
ABGR 2*	1	0.02	0.52	0.9	0.52	0.71	0.73	0.79	0.76	0.57	0.95	0.76	0.3	0.98	0.64	0.85	1
ABGR 3	1	0	0.51	0.9	0.48	0.69	0.74	0.79	0.76	0.56	0.95	0.75	0.3	0.98	0.63	0.84	1
ABGR 4	1	0	0.51	1	0	0.51	0.97	0.09	0.53	0.5	0.86	0.67	0.32	0.96	0.64	0.76	0.34
ABLA 1	0.95	0.08	0.64	0.86	0.33	0.67	0.62	0.75	0.67	0.33	0.83	0.52	0.24	0.83	0.45	0.64	0.98
ABLA 2	0.76	0.42	0.64	0.38	0.83	0.55	0.57	0.58	0.58	0.1	1	0.42	0.1	1	0.42	0.61	0.99
ABLA 3*	0.86	0.5	0.73	0.81	0.67	0.76	0.81	0.75	0.79	0.67	0.83	0.73	0.48	0.83	0.61	0.8	0
FIRS 1	0.98	0.19	0.56	0.9	0.6	0.74	0.72	0.85	0.79	0.55	0.95	0.76	0.27	0.98	0.65	0.86	1
CADE 1	0.75	0.54	0.56	0.75	0.74	0.74	0.5	0.9	0.87	0.5	0.98	0.94	0.5	1	0.96	0.73	0.97
CADE 2	0.5	1	0.96	0.5	1	0.96	0.25	1	0.94	0	1	0.93	0	1	0.93	0.72	0.98
CADE 3	0.75	0.5	0.52	0.5	0.7	0.69	0.5	0.84	0.81	0	0.96	0.89	0	1	0.93	0.61	0.93
CADE 4*	1	0.66	0.69	0.25	0.9	0.85	0	0.98	0.91	0	1	0.93	0	1	0.93	0.82	0.99
CADE 5	1	0.3	0.35	0.75	0.38	0.41	0.75	0.58	0.59	0.5	0.74	0.72	0.5	0.74	0.72	0.71	0.98
CADE 6	1	0.02	0.09	0.75	0.08	0.13	0.75	0.24	0.28	0.75	0.38	0.41	0.5	0.6	0.59	0.64	0.96
CADE 7	1	0.08	0.15	0.5	0.8	0.78	0.25	0.96	0.91	0	0.98	0.91	0	1	0.93	0.64	1
CADE 9	0.5	0.96	0.93	0.5	0.96	0.93	0.5	1	0.96	0.25	1	0.94	0	1	0.93	0.76	1
CADE 8	0.5	0.96	0.93	0.5	0.98	0.94	0.5	1	0.96	0.25	1	0.94	0	1	0.93	0.64	1
CADE 10	0.5	0.98	0.94	0.25	1	0.94	0	1	0.93	0	1	0.93	0	1	0.93	0.61	0.55
CADE 11	0.5	0.96	0.93	0.5	1	0.96	0.5	1	0.96	0	1	0.93	0	1	0.93	0.76	0
CADE 12	0.5	0.96	0.93	0.25	0.98	0.93	0.25	1	0.94	0.25	1	0.94	0	1	0.93	0.66	0.2
CADE 13	0.5	0.98	0.94	0.25	0.98	0.93	0	1	0.93	0	1	0.93	0	1	0.93	0.61	0.96
CHLA 1	0.55	0.74	0.71	0.45	0.84	0.78	0.36	0.97	0.87	0.36	0.98	0.88	0.27	1	0.88	0.62	0.44
CHNO 1	1	0	0.5	1	0	0.5	0.92	0.08	0.5	0	1	0.5	0	1	0.5	0.55	0
LAOC 1	0.89	0.27	0.37	0.68	0.71	0.7	0.5	0.9	0.83	0.39	0.93	0.85	0.36	0.95	0.85	0.74	0.83
LAOC 2	0.5	0.83	0.78	0.43	0.94	0.86	0.31	0.98	0.87	0	1	0.84	0	1	0.84	0.74	0.88
LAOC 3*	0.71	0.82	0.8	0.49	0.94	0.87	0.39	0.95	0.86	0.29	0.99	0.88	0.11	0.99	0.85	0.84	0.94
PICO 1	1	0	0.68	1	0	0.68	0.79	0.27	0.62	0.22	0.93	0.45	0.13	1	0.41	0.43	1
PICO 2	1	0	0.68	0.76	0.34	0.63	0.4	0.73	0.51	0.07	1	0.36	0.04	1	0.35	0.6	1
PICO 3*	1	0	0.68	1	0	0.68	0.98	0.2	0.73	0.88	0.54	0.77	0.78	0.85	0.8	0.83	1
PIEN 1	0.97	0.05	0.72	0.65	0.41	0.58	0.3	0.9	0.46	0.21	0.97	0.42	0.16	0.98	0.38	0.6	0
PIEN 2	1	0	0.73	1	0	0.73	0.63	0.6	0.62	0.31	0.86	0.46	0.2	0.97	0.41	0.63	0.16
PIEN 3*	0.98	0.22	0.77	0.95	0.41	0.8	0.86	0.66	0.81	0.74	0.83	0.76	0.38	0.98	0.55	0.86	1
PILA 1	0.66	0.75	0.72	0.42	0.88	0.74	0.27	0.94	0.74	0.1	0.98	0.71	0	0.99	0.69	0.73	0
PILA 2	1	0	0.3	0.87	0.37	0.52	0.81	0.49	0.59	0.77	0.58	0.64	0.68	0.66	0.67	0.75	0.03
PILA 3*	0.48	0.81	0.71	0.27	0.9	0.71	0.23	0.98	0.75	0.03	0.99	0.7	0	1	0.7	0.75	0.85
PILA 4	0.48	0.81	0.71	0.27	0.9	0.71	0.08	0.96	0.69	0.03	0.99	0.7	0	1	0.7	0.63	0.7
PILA 5	0.63	0.55	0.57	0.5	0.81	0.71	0.36	0.93	0.76	0.24	0.98	0.76	0.15	0.99	0.74	0.68	0.69
PILA 6	0.79	0.56	0.63	0.63	0.74	0.7	0.45	0.9	0.76	0.35	0.95	0.77	0.26	0.98	0.76	0.77	0
PILA 7	0.73	0.4	0.5	0.47	0.76	0.67	0.32	0.92	0.74	0.24	0.98	0.76	0.15	0.99	0.73	0.65	0.87
PILA 8	1	0	0.3	0.6	0.71	0.67	0.39	0.9	0.75	0.32	0.95	0.76	0.27	0.97	0.76	0.73	0.7
PILA 9	1	0	0.3	0.61	0.67	0.66	0.42	0.88	0.74	0.32	0.95	0.76	0.18	0.98	0.74	0.73	0.96
PILA 10*	1	0.59	0.71	0.69	0.81	0.77	0.5	0.93	0.8	0.31	0.95	0.76	0.16	0.99	0.74	0.87	1
PILA 11	0.48	0.84	0.73	0.35	0.9	0.73	0.19	0.92	0.7	0.13	0.94	0.7	0.08	0.97	0.7	0.65	0.01
PILA 12	0.71	0.46	0.53	0.56	0.73	0.68	0.31	0.9	0.72	0.1	0.97	0.7	0	1	0.7	0.65	0.74
PIMO 1	0.98	0	0.47	0.88	0.24	0.55	0.79	0.67	0.73	0.42	0.85	0.64	0.23	0.91	0.58	0.72	1
PIMO 2*	0.98	0.28	0.62	0.91	0.57	0.73	0.77	0.85	0.81	0.6	0.96	0.79	0.28	0.98	0.64	0.88	0.07
PIMO 3	1	0	0.48	0.93	0.5	0.71	0.72	0.76	0.74	0.4	0.91	0.66	0.14	0.98	0.57	0.83	0.61
PIMO 4	0.98	0.04	0.49	0.93	0.52	0.72	0.77	0.74	0.75	0.37	0.89	0.64	0.12	1	0.57	0.81	0.66
THPL 1	0.78	0.15	0.45	0.67	0.8	0.74	0.5	0.9	0.71	0.5	0.95	0.74	0.39	1	0.71	0.72	0.88
TSHE 1	0.94	0.17	0.67	0.77	0.54	0.69	0.49	0.84	0.61	0.3	0.93	0.52	0.19	0.97	0.46	0.72	0
TSHE 2*	0.99	0.18	0.71	0.98	0.4	0.78	0.9	0.68	0.82	0.71	0.82	0.75	0.42	0.94	0.61	0.87	1
TSHE 3	1	0.17	0.71	0.97	0.39	0.77	0.9	0.66	0.82	0.68	0.83	0.73	0.39	0.96	0.59	0.86	0.95
TSHE 4	1	0	0.65	1	0	0.65	0.85	0.51	0.73	0.47	0.88	0.61	0.26	0.95	0.51	0.76	0.59

Fig. 1. Heat map showing TPR (true positive rate), TNR (true negative rate), and Correct (total percent mortality predicted correctly) by mortality model for various decision criteria of P_m indicated by the value immediately following the label (0.1, 0.25, 0.5, 0.75, and 0.9). AUC and AICPts shown for model in general. AICPts is a normalizing scale for AIC among species. Darker color within species indicates a higher, and in all cases here, better value. Equation codes with asterisks are recommended models. Black lines separate species. Equation codes are defined in Table S2 and full species names are listed in Table S3.

Model	TPR.1	TNR.1	Correct.1	TPR.25	TNR.25	Correct.25	TPR.5	TNR.5	Correct.5	TPR.75	TNR.75	Correct.75	TPR.9	TNR.9	Correct.9	AUC	AICPts
ABAM: ABAM 1	0.59	0.53	0.57	0.31	0.68	0.47	0.11	0.94	0.46	0.06	1	0.46	0.05	1	0.45	0.57	0.96
ABAM: ABCO 1	0.59	0.53	0.57	0.31	0.68	0.47	0.11	0.94	0.46	0.06	1	0.46	0.05	1	0.45	0.57	0.96
ABAM: ABCO 2	0.03	1	0.44	0.03	1	0.44	0	1	0.42	0	1	0.42	0	1	0.42	0.58	0
ABAM: ABCO 3	0.08	1	0.47	0.05	1	0.45	0.05	1	0.45	0.03	1	0.44	0	1	0.42	0.57	0.07
ABAM: ABCO 4	0.94	0.21	0.63	0.33	0.83	0.54	0.04	0.98	0.44	0.02	1	0.43	0	1	0.42	0.62	1
ABAM: ABCO 5	0.8	0.34	0.6	0.17	0.87	0.47	0.02	1	0.43	0	1	0.42	0	1	0.42	0.45	0.96
ABAM: ABCO 6	0.95	0.19	0.63	0.3	0.81	0.51	0.06	1	0.44	0.02	1	0.43	0	1	0.42	0.63	1
ABAM: ABCO 7	0.83	0.26	0.59	0.11	0.91	0.45	0.03	1	0.44	0	1	0.42	0	1	0.42	0.54	0.96
ABAM: ABCO 8	1	0	0.58	0.08	1	0.47	0.02	1	0.43	0.02	1	0.43	0	1	0.42	0.71	0.98
ABAM: ABCO 9	0.47	0.81	0.61	0.08	1	0.47	0.02	1	0.43	0	1	0.42	0	1	0.42	0.71	0.87
ABAM: ABCO 10	0.73	0.43	0.6	0.33	0.85	0.55	0.03	0.98	0.43	0.02	1	0.43	0	1	0.42	0.64	0.97
ABGR: ABGR 1	0.89	0.21	0.55	0.65	0.54	0.59	0.41	0.85	0.62	0.28	0.94	0.61	0.19	0.98	0.58	0.68	0.98
ABGR: ABCO 1	0.87	0.26	0.57	0.62	0.59	0.6	0.4	0.86	0.62	0.28	0.95	0.61	0.19	0.98	0.58	0.68	0.97
ABGR: ABCO 2	0.15	0.96	0.55	0.09	0.99	0.53	0.04	1	0.51	0	1	0.49	0	1	0.49	0.63	0
ABGR: ABCO 3	0.32	0.93	0.62	0.26	0.95	0.6	0.19	0.98	0.58	0.11	0.99	0.55	0.04	1	0.51	0.7	0.27
ABGR: ABCO 4	0.92	0.43	0.68	0.62	0.73	0.67	0.32	0.94	0.63	0.19	0.98	0.58	0.12	0.99	0.55	0.77	1
ABGR: ABCO 5	0.88	0.26	0.57	0.66	0.63	0.65	0.29	0.94	0.61	0.18	0.98	0.57	0.12	1	0.55	0.7	0.98
ABGR: ABCO 6	0.87	0.48	0.68	0.4	0.9	0.65	0.25	0.98	0.61	0.15	0.99	0.57	0.1	1	0.54	0.78	0.96
ABGR: ABCO 7	0.89	0.23	0.57	0.35	0.89	0.61	0.25	0.98	0.6	0.15	0.99	0.56	0.09	1	0.53	0.68	0.94
ABGR: ABCO 8	1	0	0.51	0.37	0.87	0.62	0.25	0.96	0.6	0.17	0.99	0.57	0.1	1	0.54	0.71	0.96
ABGR: ABCO 9	0.69	0.63	0.66	0.35	0.91	0.62	0.23	0.98	0.6	0.15	0.99	0.57	0.1	1	0.54	0.71	0.88
ABGR: ABCO 10	0.94	0.31	0.63	0.58	0.8	0.69	0.29	0.96	0.62	0.2	0.98	0.59	0.13	1	0.56	0.79	1
ABLA: ABLA 1	0.95	0.08	0.64	0.86	0.33	0.67	0.62	0.75	0.67	0.33	0.83	0.52	0.24	0.83	0.45	0.64	0.9
ABLA: ABLA 2	0.76	0.42	0.64	0.38	0.83	0.55	0.57	0.58	0.58	0.1	1	0.42	0.1	1	0.42	0.61	0.88
ABLA: ABLA 3	0.86	0.5	0.73	0.81	0.67	0.76	0.81	0.75	0.67	0.83	0.73	0.48	0.83	0.61	0.36	0.5	1
ABLA: ABCO 1	0.95	0.08	0.64	0.81	0.33	0.64	0.48	0.75	0.58	0.33	0.83	0.52	0.24	0.83	0.45	0.64	0.89
ABLA: ABCO 2	0.24	0.83	0.45	0.19	0.83	0.42	0	0.92	0.33	0	1	0.36	0	1	0.36	0.64	0.07
ABLA: ABCO 3	0.33	0.83	0.52	0.33	0.83	0.52	0.24	0.83	0.46	0.14	0.92	0.42	0.05	0.92	0.36	0.61	0
ABLA: ABCO 4	0.86	0.33	0.67	0.52	0.58	0.55	0.29	1	0.55	0.14	1	0.45	0.1	1	0.42	0.62	0.83
ABLA: ABCO 5	0.9	0.25	0.67	0.43	0.33	0.39	0.24	0.92	0.48	0.1	1	0.42	0.05	1	0.39	0.51	0.82
ABLA: ABCO 6	0.76	0.58	0.7	0.38	0.83	0.55	0.24	1	0.52	0.1	1	0.42	0.1	1	0.42	0.75	0.8
ABLA: ABCO 7	0.86	0.25	0.64	0.33	0.83	0.52	0.14	0.92	0.42	0.1	1	0.42	0.05	1	0.39	0.58	0.79
ABLA: ABCO 8	1	0	0.64	0.43	0.83	0.58	0.19	0.92	0.46	0.14	1	0.45	0.1	1	0.42	0.64	0.86
ABLA: ABCO 9	0.76	0.42	0.64	0.38	0.83	0.55	0.14	0.92	0.42	0.1	1	0.42	0.1	1	0.42	0.64	0.73
ABLA: ABCO 10	0.9	0.25	0.67	0.48	0.67	0.55	0.29	0.92	0.52	0.1	1	0.42	0.05	1	0.39	0.71	0.83
CHLA: CHLA 1	0.55	0.74	0.71	0.45	0.84	0.78	0.36	0.97	0.87	0.36	0.98	0.88	0.27	1	0.88	0.62	0.96
CHLA: CHNO 1	1	0.02	0.17	0.64	0.19	0.26	0.64	0.71	0.7	0.45	0.91	0.84	0.36	0.97	0.87	0.63	0.72
CHLA: THPL 1	0.73	0.17	0.26	0.64	0.64	0.64	0.46	0.79	0.74	0.36	0.97	0.87	0.36	0.97	0.87	0.62	0.86
CHLA: CADE 1	0.64	0.66	0.65	0.45	0.81	0.75	0.36	0.95	0.86	0.36	0.97	0.87	0.36	0.98	0.88	0.62	0.94
CHLA: CADE 2	0.27	0.98	0.87	0.18	0.98	0.86	0.09	1	0.86	0	1	0.84	0	1	0.84	0.65	0.03
CHLA: CADE 3	0.64	0.57	0.58	0.55	0.64	0.62	0.46	0.79	0.74	0.45	0.93	0.86	0	0.98	0.83	0.62	0.7
CHLA: CADE 4	0.73	0.62	0.64	0.45	0.88	0.81	0	0.98	0.83	0	1	0.84	0	1	0.84	0.67	0.93
CHLA: CADE 5*	0.82	0.43	0.49	0.73	0.52	0.55	0.73	0.64	0.65	0.55	0.71	0.68	0.45	0.79	0.74	0.7	0.07
CHLA: CADE 6	1	0	0.16	0.82	0.12	0.23	0.73	0.33	0.39	0.64	0.57	0.58	0.55	0.69	0.67	0.62	0
CHLA: CADE 7	1	0.03	0.19	0.36	0.86	0.78	0.09	1	0.86	0	1	0.84	0	1	0.84	0.62	0.99
CHLA: CADE 8	0.45	0.97	0.88	0.36	0.98	0.88	0.27	0.98	0.87	0.18	1	0.87	0.09	1	0.86	0.86	1
CHLA: CADE 9	0.45	0.98	0.9	0.36	0.98	0.88	0.18	0.98	0.86	0.09	1	0.86	0.09	1	0.86	0.74	0.85
CHLA: CADE 10	0.45	0.98	0.9	0.27	0.98	0.87	0.27	1	0.88	0.09	1	0.86	0	1	0.84	0.85	0.97
CHLA: CADE 11	0.36	0.98	0.88	0.18	0.98	0.86	0.18	0.98	0.86	0.09	1	0.86	0	1	0.84	0.74	0.91
CHLA: CADE 12	0.45	0.98	0.9	0.27	0.98	0.87	0.27	0.98	0.87	0.18	1	0.87	0.09	1	0.86	0.7	0.95
CHLA: CADE 13	0.45	0.98	0.9	0.27	0.98	0.87	0.38	1	0.88	0.18	1	0.87	0	1	0.84	0.86	0.98
CHNO: CHLA 1	0.77	0.46	0.62	0.08	0.85	0.46	0	1	0.5	0	1	0.5	0	1	0.5	0.55	0.94
CHNO: CHNO 1	1	0	0.5	1	0	0.5	0.92	0.08	0.5	0	1	0.5	0	1	0.5	0.55	1
CHNO: THPL 1	1	0	0.5	0.92	0.08	0.5	0.77	0.15	0.46	0	1	0.5	0	1	0.5	0.55	1
CHNO: CADE 1	0.92	0.08	0.5	0.54	0.62	0.58	0	1	0.5	0	1	0.5	0	1	0.5	0.55	0.97
CHNO: CADE 2	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0.52	0
CHNO: CADE 3	1	0.08	0.54	1	0.08	0.54	0.77	0.15	0.46	0.69	0.54	0.62	0.38	0.85	0.62	0.61	0.96
CHNO: CADE 4	0.69	0.38	0.54	0	0.92	0.46	0	1	0.5	0	1	0.5	0	1	0.5	0.57	0.93
CHNO: CADE 5	0.69	0.38	0.54	0.46	0.77	0.62	0.15	0.92	0.54	0	0.92	0.46	0	0.92	0.46	0.64	0.89
CHNO: CADE 6	1	0	0.5	0.23	0.85	0.54	0.08	0.92	0.5	0.08	0.92	0.5	0	0.92	0.46	0.55	0.91
CHNO: CADE 7	0.38	0.77	0.58	0	0.92	0.46	0	1	0.5	0	1	0.5	0	1	0.5	0.55	0.92
CHNO: CADE 8	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0.88	0.83
CHNO: CADE 9	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0.52	0.78
CHNO: CADE 10	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0.86	0.8
CHNO: CADE 11	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0.52	0.76
CHNO: CADE 12	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0.75	0.78
CHNO: CADE 13	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0	1	0.5	0.86	0.82
THPL: CHLA 1	0.56	0.9	0.74	0.5	0.95	0.74	0.39	0.95	0.68	0.39	1	0.71	0.28	1	0.66	0.72	0.91
THPL: CHNO 1	1	0	0.47	0.78	0.15	0.45	0.61	0.9	0.76	0.5	0.95	0.74	0.44	0.95	0.71	0.72	1
THPL: THPL 1	0.78	0.15	0.45	0.67	0.8	0.74	0.5	0.9	0.71	0.5	0.95	0.74	0.39	1	0.71	0.72	0.99
THPL: CADE 1	0.67	0.85	0.76	0.5	0.9	0.71	0.44	0.95	0.71	0.39	1	0.71	0.39	1	0.71	0.72	0.94
THPL: CADE 2	0.33	1	0.68	0.33	1	0.68	0.17	1	0.6	0	1	0.53	0	1	0.53	0.75	0
THPL: CADE 3	0.67	0.75	0.71	0.44	0.8	0.63	0.33	0.9	0.63	0.28	0.9	0.61	0.28	1	0.66	0.68	0.77
THPL: CADE 4	0.5	0.9	0.71	0.22	0.95	0.61	0	1	0.53	0	1	0.53	0	1	0.53	0.74	0.79
THPL: CADE 5	0.72	0.85	0.79	0.72	0.85	0.79	0.5	0.9	0.71	0.22	0.95	0.61	0.17	0.95	0.58	0.75	0.85
THPL: CADE 6	1	0	0.47	0.78	0.55	0.66	0.67	0.75	0.71	0.33	0.85	0.61	0.28	0.9	0.61	0.7	0.98
THPL: CADE 7	0.83	0.25	0.53	0.11	1	0.58	0	1	0.53	0	1	0.53	0	1	0.53	0.7	0.9
THPL: CADE 8	0.5	0.95	0.74	0.33	0.95	0.66	0.22	0.95	0.6	0.22	1	0.63	0.06	1	0.55	0.8	0.84
THPL: CADE 9	0.44	0.95	0.71	0.33	0.95	0.66	0.22	0.95	0.6	0.11	1	0.58	0.06	1	0.55	0.83	0.74
THPL: CADE 10	0.22	0.95	0.61	0.17	0.95	0.58	0.17	0.95	0.58	0	1	0.53	0	1	0.53	0.78	0.75
THPL: CADE 11	0.33	0.95	0.66	0.28	0.95	0.63	0.17	1	0.6	0.06	1	0.55	0	1	0.53	0.83	0.77
THPL: CADE 12	0.33	0.95	0.66	0.22	0.95	0.61	0.17	0.95	0.58	0.06	1	0.55	0	1	0.53	0.83	0.76
THPL: CADE 13	0.22	0.95	0.61	0.17	0.95	0.58	0.17	0.95	0.58	0	1	0.53	0	1	0.53	0.78	0.76

Fig. 2. Heat map showing TPR (true positive rate), TNR (true negative rate), and Correct (total percent mortality predicted correctly) by mortality model for various decision criteria of P_m indicated by the value immediately following the label (.1, 0.25, 0.5, 0.75, and 0.9). AUC and AICPts shown for model in general. AICPts is a normalizing scale for AIC among species. Darker color within species indicates a higher, and in all cases here, better value. Equation codes with asterisks are recommended models. Black lines separate species. First four letter code indicates the species' data used. Second code with numerals indicates the equation validated. Equation codes with asterisks are recommended models. Black lines separate species. Equation codes are defined in Table S2 and full species names are listed in Table S3.

ria were more accurate, with a %C of 71% and a FPR of 42%. These criteria also overpredict mortality, as did the Scott guidelines, but to a much lesser extent. Our new guidelines of CVS $\geq$ 70% or CKR $\geq$ 3 correctly classified 79% of trees with a FPR of 21% (Table 5). This is 13% higher overall accuracy than the best logistic model at $P_m = 0.5$.

3.1.3. Grand fir

Grand fir mortality was monitored for 750 trees at four fires on two national forests (Tables S1 and S3). CVS and CKR were higher in trees that died compared to surviving trees, but DBH did not differ by status (Table 3, Figs. S2–S4). No species-specific model exists for grand fir. We validated the accuracy of FOFEM 5 and the white fir equations to predict grand fir mortality (Table S2). The FOFEM 5 model for grand fir predicted survival better than mortality and had a relatively low AUC value of 0.68 (Fig. 1). Three models, ABCO 4, ABCO 6, and ABCO 10, developed for white fir were fair candidates to describe post-fire mortality of grand fir, with an AUC of 0.78, 0.79, and 0.77, respectively (Fig. 2). Of these, ABCO 6 had both the lowest AIC and the best TPR across multiple cutoffs, while maintaining comparable %C.

We developed three new mortality models for grand fir:

$$\mathrm{ABGR\ 2}: P_m = 1/\left(1 + e^{(-(-2.3380 + 0.2094 * \mathrm{CKR}^2 + 3.6570e^6 * \mathrm{CVS}^3 + 0.1663 * \mathrm{BSH} + 0.06420 * \mathrm{Precrown}))}\right)$$

$$\mathrm{ABGR\ 3}: P_m = 1/\left(1 + e^{(-(-1.9565 + 0.2031 * \mathrm{CKR}^2 + 3.5520e^6 * \mathrm{CVS}^3 + 0.1853 * \mathrm{BSH}))}\right)$$

$$\mathrm{ABGR\ 4}: P_m = 1/\left(1 + e^{(-(0.006416 + 3.7180e^6 * \mathrm{CVS}^3 + 0.19174 * \mathrm{BSH} - 0.01007 * \mathrm{Precrown}))}\right)$$

ABGR 2 had an AUC of 0.85, a %C of 76%, a FPR of 21%, and an AIC of 723 while ABGR 3 had an AUC of 0.85, a %C of 76%, a FPR of 21%, and an AIC of 716. The addition of more variables to ABGR 3 decreased AIC by less than 2. Thus, though ABGR 3 fits the data best, the simpler ABGR 2 can be used with negligible loss in predictive accuracy. ABGR 4 does not include a term for CKR, which greatly reduces model accuracy (Fig. 1). ABGR 4 has an AUC of 0.76, a %C of just 53%, and a FPR of 91%.

The Scott guidelines did not perform well, overpredicting mortality with a FPR of 93% and an overall %C of 54% (Table 4). We developed a new threshold, with a %C of 76%, a FPR of 20%, and a FNR of 28% when the tree has a CVS $\geq$ 60% or a CKR $\geq$ 3 (Table 5). The new threshold performs similarly to the best logistic regression model, ABGR 2 (Table 5).

3.1.4. Subalpine fir

Subalpine fir mortality was measured on 33 trees at five fires on four national forests (Tables S1 and S3). There was no difference in DBH or CVS between live and dead trees, but dead trees had higher CKR values than live trees (Table 3, Figs. S2–S4). In addition to the FOFEM 5 model, two models from Hood and Lutes (2017) were available to validate (Tables 2 and S2). ABLA 1 and ABLA 2 did not perform well, with an AUC of 0.64 and 0.61, respectively (Fig. 1). Each predicted total mortality and survival at a similar rate for most cutoffs. However, the AUC of 0.88 for ABLA 3, which includes CVS and CKR, indicates that it is not only a better candidate than the others, but also adequately predicts individual tree survival. Because of the limited number of models available for subalpine fir, we also validated the white fir models against the subalpine fir data. Only one of these equations, ABCO 6, performed adequately, with an AUC of 0.75 (Fig. 2), but it was not as accurate as ABLA 3. Therefore, we do not recommend using white fir models to predict subalpine fir post-fire tree mortality. Our sample size was low for subalpine fir so additional validation is necessary to fully evaluate the robustness of these existing models over a broader range of injuries and sizes.

The Scott guidelines predicted all trees to die, giving a FPR of 100% and a 64% total correct rate (Table 4). There were not enough trees in this dataset to create a reliable novel model or guideline set. Thus, we recommend using ABLA 3 to predict individual subalpine fir post-fire mortality in the Pacific Northwest.

3.1.5. Firs

Because of the similarities between white fir and grand fir, we pooled the two into one group which we called "Firs". Though the white fir threshold guidelines are similar to those of grand fir, they yielded sufficiently different results that they should be considered separately. Combining them into one Firs category with mortality predicted by CVS $\geq$ 0.6 or CKR $\geq$ 3 gives a %C of 77% and a FPR of 24%. This is similar to that of grand fir, but slightly less accurate than the guidelines for white fir, which can survive higher levels of crown scorch.

A logistic analysis of Firs yielded an equation which improved both white fir and grand fir classification, but at the expense of additional terms. The best model utilizes six terms:

$$\mathrm{FIRS\ 1}: P_m = 1/\left(1 + e^{(-(-1.0163 + 0.1887 * \mathrm{CKR}^2 + 3.7080e^4 * \mathrm{CVS}^3 + 0.1217 * \mathrm{BSH} + 0.9390 * \mathrm{BTL} - 1.6255 * \mathrm{CR} - 0.01330 * \mathrm{DBH}))}\right)$$

This extra data collection yields a model with a %C of 79%, an AIC of 1529, and an AUC of 0.86 (Fig. 1). These results are quite good, but may or may not be worth the extra data collection and computational expense compared to respective recommended models for white fir and grand fir.

3.2. "Cedars"

3.2.1. Incense cedar

Incense cedar mortality was measured for 54 trees at five fires on four national forests in Oregon (Tables S1 and S3). There was no clear distinction in DBH, CVS, or DBH between live and dead trees (Table 3, Figs. S2–S4). There were 13 logistic models available to predict post-fire mortality for incense cedar (Tables 2 and S2). Of these, CADE 4 from Regelbrugge and Conard (1993), which includes only DBH and CH, performed best (AUC = 0.82; Fig. 1). Upon inspection of the data at multiple cutoffs, it at first appears that this may be a case of a model underpredicting mortality on a dataset with few tree deaths. However, it predicted tree death at lower cutoff, indicating that the model performs well. Wagener's guidelines include incense cedar, but the Scott guidelines do not (Table 2). Wagener's criteria performed moderately well, with a %C of 70% and a FPR of 28% (Table 4). With just four tree deaths, the data were not well distributed enough to create new models or threshold guidelines. Additional validation is necessary to assess the robustness of these models over a full range of tree characteristics and fire injury (Table 3).

Table 4
Model accuracy using Scott (2002), Scott et al. (2003) guidelines and Wagener (1961) criteria to predict probability of survival within 3 years post-fire in Oregon and Washington. Full species names are listed in Table S3. TPR = true positive rate; FPR = false positive rate; TNR = true negative rate; FNR = false negative rate.

Code	Dead	Live	Predicted Low	Predicted Moderate	Predicted High	Predicted Dead	Predicted Alive	TPR %	FPR %	TNR %	FNR %	Correct %
Scott guidelines												
ABLA S	21	12	32	1	0	33	0	100	100	0	0	64
ABCO S	396	524	801	102	17	878	42	100	92	8	0	46
ABGR S	381	369	661	80	8	723	27	99	93	7	1	52
PICO S	89	41	119	9	2	126	4	97	98	2	3	67
PIMO S	43	46	0	45	44	13	76	16	13	87	84	53
PIEN S	153	58	173	34	4	204	7	100	88	12	0	76
LAOC S	72	377	1	219	229	34	415	26	4	96	74	85
Wagener's criteria												
ABCO W	396	524	NA	NA	NA	568	352	88	42	58	12	71
CADE W	4	50	NA	NA	NA	16	38	50	28	72	50	70
PILA W	62	144	NA	NA	NA	111	95	71	47	53	29	59

Table 5
Post-fire mortality and survival thresholds and accuracy (observed compared to predicted) identified using piecewise regression. Thresholds with 'or' mean any listed criterion can be used, while thresholds with 'and' mean all criteria must be met. Total correct (%C) values are compared against the best performing logistic regression model using a decision criterion = 0.5 to determine mortality and survival from Figs. 1 and 2, with positive Δ %C values indicating improved performance over logistic regression models and negative values indicating worse performance. TPR = true positive rate; FPR = false positive rate; TNR = true negative rate; FNR = false negative rate. Full species names are listed in Table S3 and variable descriptions in Table 1.

Species	Mortality thresholds	Survival thresholds	Obs. dead	Obs. live	Pred. dead	Pred. alive	TPR %	FPR %	TNR %	FNR %	% C	Best logistic model	Best logistic % C	Δ % C
Firs														
ABAM	CKR = 4	CKR ≤ 3	64	47	58	53	70	28	72	30	71	ABAM 3	66	5
ABCO	CVS ≥ 70% or CKR ≥ 3	CVS < 70% and CKR ≤ 2	396	524	424	496	79	21	79	21	79	ABCO 10	66	13
ABGR	CVS ≥ 60% or CKR ≥ 3	CVS < 60% and CKR ≤ 2	381	369	349	401	72	20	80	28	76	ABGR 2	76	0
Pines														
PICO	CVS ≥ 40% or CKR ≥ 3 or IB = 1	CVS < 40% and CKR ≤ 2 and IB = 0	89	41	101	29	97	37	63	3	86	PICO 3	73	13
PIEN	CVS ≥ 75% or CKR ≥ 3	CVS < 75% and CKR ≤ 2	153	58	144	67	84	26	74	16	82	PIEN 3	81	1
PILA	RCH ≥ 0.3	RCH < 0.3	62	144	55	151	55	15	85	45	76	PILA 10	80	-4
PILA	CVS ≥ 70%	CVS < 70%	62	144	30	176	37	5	95	63	79	PILA 10	80	-1
PIMO	CKR = 4 and CVS > 10%	CKR ≤ 3 or CVS ≤ 10%	43	46	30	59	63	7	93	37	79	PIMO 2	81	-2
PIMO	CVS > 30%	CVS ≤ 30%	43	46	43	46	74	24	76	26	75	PIMO 2	81	-6
Larch														
LAOC	PCLS ≥ 50% or CKR = 4	PCLS < 50% and CKR ≤ 3	72	377	63	386	65	4	96	35	91	LAOC 3	86	5
Hemlock														
TSHE	CVS ≥ 20% or CKR = 4	CVS < 20% and CKR ≤ 3	370	198	438	130	93	48	52	7	79	TSHE 3	82	-3

3.2.2. Port orford cedar

Port Orford cedar were measured at two fires in the Rogue River-Siskiyou National Forest for a total of 69 trees (Tables S1 and S3). There was no difference in DBH or CVS between live and dead trees, but CKR was higher in dead trees than live (Table 3, Figs. S2–S4). There are no species-specific models for Port Orford cedar. We validated the predictive accuracy of FOFEM 5 and the incense cedar equations for post-fire Port Orford cedar mortality (Table 2). The FOFEM 5 model for Port Orford cedar predicted very high survival (Fig. 1). The percent of trees correctly predicted to die only breeched 50% at a cutoff of $P_m = 0.10$. TNR was consistently high due to underpredicting mortality. Because only 16% of the trees died, this near 100% prediction of trees living yielded high total percent correct for most cutoffs despite poor mortality prediction (Table 3). AUC was low at 0.62 (Fig. 1). Though three incense cedar models appeared to predict post-fire mortality well, this was due to the models underpredicting mortality on a dataset skewed toward survival (Fig. 2). The high AUC values of over 0.85 were artificially inflated by consistent survival predictions on a data set with only 16% mortality. CADE 5 had a fair AUC of 0.70, and also showed good TPR and TNR across all cutoffs (Fig. 2). This is the recommended model for Port Orford cedar, though its moderate performance should be taken into account if used. Additional validation with a more thorough dataset is necessary to confirm the robustness of this model. There were not enough trees sampled to adequately define new models or guidelines.

3.2.3. Alaska cedar

Alaska cedar were not well represented within the dataset. Of the 26 trees measured, all were from one fire in the Olympic National Forest, and none exhibited crown volume scorch greater than 20% (Tables S1 and S3). While CKR was higher for dead trees than surviving trees, CVS was slightly lower for dead trees than live (Table 3, Figs. S2–S4); likely an artifact of the low sample size. DBH was not significantly different between live trees and dead (Table 3, Figs. S2–S4). No species-specific mortality models exist for Alaska cedar (Table 2). We validated the predictive accuracy of CHNO 1, the FOFEM 5 model, and of the incense cedar equations in assessing Alaska cedar mortality. CHNO 1 performed poorly, predicting only 50% of tree mortality correctly (Fig. 1). The FPR was 92%, and the AUC was 0.55. At first glance, three incense cedar models appear to be excellent, with AUCs over 0.85 (Fig. 2). However, a closer inspection of the accuracy at various cutoffs revealed that the models simply did not predict any tree mortality. Since both %C and AUC are based on sensitivity and specificity, the consistent 100% TNR (and therefore 0% FPR) artificially inflates the %C and AUC values. This examination indicated that the models were not adequate descriptors of post-fire mortality in Alaska cedar. We do not recommend using the FOFEM 5 model or any incense cedar models to predict post-fire mortality of Alaska cedar, but, given the small size and narrow range of our dataset, further validation is needed to confirm this.

3.2.4. Western redcedar

Western redcedar mortality was sampled for 38 trees at two fires in the Umpqua National Forest (Tables S1 and S3). There was no clear distinction in DBH, CVS, or CKR between live and dead trees (Table 3, Figs. S2–S4). Mortality was 47% for the 38 trees studied. No species-specific models exist for western redcedar (Table 2). We validated the accuracy of FOFEM 5 (THPL1) and of the available incense cedar equations in predicting post-fire western redcedar mortality. FOFEM 5 was a fair performer with an AUC of 0.72 and a %C of 71% (Fig. 1). In fact, THPL 1 had a %C of over 70% for all cutoffs except $P_m = 0.1$. This model may be adequate in some situations, provided the uncertainty in its predictions are taken into account. Several of the 13 incense cedar equations showed a fair to good AUC, but these are likely artifacts of very high TNR and very low TPR (Fig. 2). THPL 1 is then the recommended model for western redcedar. Additional validation with a larger dataset is necessary to validate the robustness of this equation. We did not have enough data to effectively develop new models or thresholds for western redcedar.

3.3. Pines

3.3.1. Lodgepole pine

Lodgepole pine were studied at four fires on three national forests for a total of 130 trees (Tables S1 and S3). Both CKR and CVS were substantially higher in dead trees than in live trees (Table 3, Figs. S2–S4). There was no difference in DBH. In addition to FOFEM 5 (PICO 1), two logistic models from Hood and Lutes (2017) were available for validation. PICO 1 and PICO 2 utilized only DBH and CVS and performed very poorly, with an AUC below 0.60 (Fig. 1). PICO 3, which included a beetle term, was very accurate, producing an AUC of 0.827 and reasonable hit rates for each cutoff. The lodgepole pine from three of the fires in the dataset had significant beetle infestation, so it is somewhat expected that those models which did not include a beetle component were not accurate. PICO 3 is the recommended model for lodgepole pine.

The Scott guidelines include lodgepole pine. When the moderate level was split, the guidelines have a %C of 67% (Table 4). Mortality was greatly overpredicted with a FPR of 98%. New guidelines we developed assume tree mortality if CVS $\geq$ 40% or CKR $\geq$ 3 or IB = 1 (Table 5). This gave a %C of 86% and a FPR of 37%. This has a 13% higher total percent predicted correctly at $P_m = 0.5$ than the best logistic model (Table 5).

3.3.2. Sugar pine

Sugar pine were measured at five fires on three national forests for a total of 206 trees (Tables S1 and S3). There was no difference in DBH or CKR between live and dead trees, but CVS was higher in dead trees than in live (Table 3, Figs. S2–S4). Twelve logistic models were validated for sugar pine (Table 2). Four models were reasonably accurate (Fig. 1). At 0.87, PILA 10, which includes a CKR and a BTL term, had the highest AUC by a wide margin (Table 2). It additionally showed high %C at all cutoffs (Fig. 1). PILA 6 also includes a beetle term, RTB, and had a high AUC of 0.77 (Table 2). Univariate analysis demonstrated that BTL was strongly tied to mortality, affecting model prediction more than any other term we tested (data not shown). It is strongly recommended to use this model when possible. The two strong models without beetle terms, PILA 3 and PILA 2, have the same AUC of 0.754 and very similar AIC (Fig. 1). However, PILA 3 displayed both better %C and lower FPR at all cutoffs, and is the recommended model when beetle infestation or cambium mortality data are not available.

Wagener's criteria were available for sugar pine, but did not perform well (Tables 2 and 4). They produced only 59% overall accuracy by overpredicting mortality. Two different thresholds stood out when developing new guidelines (Table 5). The first assumes mortality if RCH $\geq$ 0.3, yielding a %C of 76% and a FPR of 15%. The second performs slightly better overall, with a %C of 79% and a FPR of 5% when assuming mortality when CVS $\geq$ 70%. This is close to the overall accuracy at $P_m = 0.5$ of the best logistic model, PILA 10.

3.3.3. Western white pine

Western white pine mortality was studied for 89 trees at four fires on three national forests in Oregon (Tables S1 and S3). Both CVS and CKR were higher in dead trees than in live trees; DBH was similar in both groups (Table 3, Figs. S2–S4). There are no species-specific mortality models for western white pine; we validated the predictive accuracy of FOFEM 5 model (PIMO 1, Table 2). PIMO 1 performed fairly, with an AUC of 0.72 and a %C only below 50% for $P_m = 0.1$ (Fig. 1). Though this is tolerable, we developed new logistic models:

$$\text{PIMO 2}: P_m = 1/(1 + e^{(-(-3.6536+0.04311*CVS+0.2101*CKR^2))})$$

$$\text{PIMO 3}: P_m = 1/(1 + e^{(-(-1.5130+0.04281*CVS))})$$

PIMO 2 had an AUC of 0.88 and a %C of 81% and is the recommended logistic model for western white pine in the Pacific Northwest (Fig. 1). PIMO 3 has an AUC of 0.83 and a %C of 74%, and is recommended when CKR is not available.

The Scott guidelines for western white pine significantly underpredicted mortality at 87% (Table 4). This artificially inflated the %C to a still low 53%. We thus developed new threshold guidelines for western white pine (Table 5). Assuming trees with greater than 10% crown volume scorch and four cambium quadrants killed would die, the new guidelines had a %C of 79%, and a FPR of just 6.5%. Alternatively, we can assume that any trees with greater than 30% CVS will die with a %C of 75% and a FPR of 24%. This represents a 2% and 6% lower total percent correct, respectively, than the best logistic model at $P_m = 0.5$.

3.4. Spruce

3.4.1. Engelmann spruce

Engelmann spruce were evaluated at four fires on two national forests for a total of 211 trees (Tables S1 and S3). CKR was higher for dead trees than for live (Table 3, Figs. S2–S4). There was no significant difference in DBH or CVS between live and dead trees. There were three logistic models available for Engelmann spruce: the FOFEM 5 model (PIEN 1) and two equations from Hood and Lutes (2017, Table 2). PIEN 1 and PIEN 2 models performed poorly, with AUCs under 0.65 (Fig. 1). PIEN 3, which has a cambium mortality term, accurately predicted post-fire Engelmann spruce mortality and survival, with an AUC of 0.86 and %C greater than 75% for all cutoffs under $P_m = 0.9$ (Table 2, Fig. 1). This is the recommended logistic model for Engelmann spruce.

The Scott guidelines can be used for Engelmann spruce (Table 2). Overall accuracy was artificially exaggerated by the high mortality rate in the observed population coupled with the overestimation of mortality by the guidelines. The %C was 76%, but the FPR was 88% (Table 4). Our new guidelines predict mortality when CVS $\geq$ 75% or CKR $\geq$ 3, giving a %C of 82% and a FPR of 26% (Table 5). This is 1% better overall accuracy than the best logistic model at $P_m = 0.5$.

3.5. Larch

3.5.1. Western larch

Western larch mortality was measured for 449 trees at six fires on five national forests (Tables S1 and S3). DBH was smaller in dead trees than in live trees (Table 3). CVS and CKR were higher in dead trees than in live trees. In addition to the FOFEM 5 model (LAOC 1), two logistic models from Hood and Lutes (2017) were available for validation (Table 2). LAOC 1 and LAOC 2, based on DBH and CVS, performed similarly, with an AUC = 0.74 (Fig. 1). LAOC 1 had a higher AIC and a more even %C across cutoffs than LAOC 2, and is therefore the recommended model when CKR is not available. LAOC 3, which does have a CKR term, was quite accurate in predicting post-fire mortality (Table 1, Fig. 1). The AUC of 0.84 is, however, deceptive. The model overpredicted survival quite a bit, and the large proportion of larch that survived inflates the accuracy measures. It did, however, still predict some mortality at each cutoff and is the recommended model. Its tendency to underpredict mortality should be considered if management objectives involve removing all trees that will die.

The Scott guidelines also did fairly well predicting western larch survival (Table 4). They produced a %C of 85%, a FPR of 4%, and a FNR of 74%. This false negative rate was quite high, indicating that the high percent of larch that survived may have skewed the overall classification accuracy. Our new guidelines with mortality predicted by PCLS $\geq$ 50 or CKR = 4 yielded a %C of 91% a FPR of 4%, and a FNR of 35% (Table 5). This is 5% higher overall accuracy than the best logistic model at $P_m = 0.5$.

3.6. Hemlock

3.6.1. Western hemlock

Western hemlock were studied at seven fires on four national forests for a total of 568 trees (Tables S1 and S3). The DBH of dead trees was smaller than that of live trees (Table 3). CVS and CKR were higher in dead trees than in live trees. No species-specific mortality equations exist for western hemlock (Table 2). We validated the accuracy of FOFEM 5 (TSHE 1) in predicting post-fire western hemlock mortality. TSHE 1 produced an AUC of 0.72 (Fig. 1). As with western white pine and western redcedar, this may be adequate in some situations, but the uncertainty of the model must be taken into account if used. We therefore developed new logistic models for western hemlock mortality of:

$$\mathrm{TSHE\ 2}: \mathrm{P_m} = 1/(1+\mathrm{e}^{(-(-0.4045+0.2013*\mathrm{CKR}^2+1.9783*\mathrm{BTL}-0.03004*\mathrm{DBH}+0.02587*\mathrm{CVS}-2.8540*\mathrm{CR}))})$$

$$\mathrm{TSHE\ 3}: \mathrm{P_m} = 1/(1+\mathrm{e}^{(-(-1.7316+0.1938*\mathrm{CKR}^2+1.7015*\mathrm{BTL}-0.02957*\mathrm{DBH}+0.02000*\mathrm{CVS}))})$$

$$\mathrm{TSHE\ 4}: \mathrm{P_m} = 1/(1+\mathrm{e}^{(-(1.1131-0.01164*\mathrm{DBH}+0.03556*\mathrm{CVS}-1.2588*\mathrm{CR}))})$$

New equation THSE 2 has an AUC of 0.86, %C of 82%, and FPR of 34% (Fig. 1). TSHE 3 has an AUC of 0.87, %C of 82%, and FPR of 32%. Because the accuracy of TSHE 2 is so close to that of TSHE 3, we used AIC to determine the recommended model. TSHE 3 has an AIC of 481, while TSHE 2 has an AIC of 499. This 18 ΔAIC is large enough to assume that the data are better described by TSHE 3 than TSHE 2, thus TSHE 3 is the recommended model. TSHE 4, the model with no CKR or BTL terms, has an AUC of 0.76, a %C of 73%, and a rather high FPR of 49%.

Neither Wagener's criteria nor the Scott guidelines were developed for western hemlock (Table 2). New thresholds show that CVS $\geq$ 20% or CKR = 4 results in a %C of 79%, FNR of 7%, and FPR of 48% (Table 5). Though this FPR is still high, we were unable to lower it without lowering the overall classification accuracy. These guidelines have an overall accuracy 3% lower than that of the best logistic model at $P_m = 0.5$.

3.7. Results summary

Choosing an appropriate post-fire tree mortality model relies heavily on management objectives. Overall accuracy may be less important than simplicity of data collection. In some cases overprediction of mortality (i.e., higher FPR) may be acceptable; in other cases more conservative thresholds that minimize FPR and leave standing dead trees is desired. The model that most adequately describes the data may still over- or under-predict mortality more than another, less overall accurate model. Furthermore, logistic regression models can be difficult to apply to individual trees (e.g., continuous probabilities must be converted to binary values) but useful for examining expected stand-level mortality by species and size classes (Reinhardt et al., 2009; Hood et al., 2010; Woolley et al., 2012) .

ROC measures and total events correctly predicted (%C) are based on TPR and FPR. When a dataset is highly skewed, either because most of the trees survived or most did not, the values for AUC and %C can be artificially inflated. For example, only four of the 54 incense cedar died (Table 3). Thus, if a model predicts all of the trees survive, the FPR (and its inverse, TNR) is very good, simply because if none of the trees are predicted to die, there can be no false positives. Those models that display such behavior should be examined logically before any determination is made as to efficacy.

Though FOFEM 5 predicts mortality for all tree species in the USA, its accuracy has been validated for very few species. FOFEM 5 was not the recommended model for any of the 14 species we tested. It performed very poorly (AUC < 0.6) for Pacific silver fir, Alaska cedar, and lodgepole pine, and poorly (AUC < 0.7) for grand fir, subalpine fir, Port Orford cedar, and Engelmann spruce. Besides FOFEM 5, many other models have been developed with various degrees of validation. Virtually no research has been done in the Pacific Northwest for species other than Douglas-fir and ponderosa pine. Our validation showed CADE 4 (Regelbrugge and Conard, 1993), ABCO 10, ABLA 3, LAOC 3, PICO 3, PIEN 3, and PILA 10 (Hood and Lutes, 2017) perform better than other models. All of these models except CADE 4 have cambium kill and crown injury terms.

We developed new models for Pacific silver fir (ABAM 2, ABAM 3), grand fir (ABGR 2, ABGR 3, ABGR 4), the combined white and grand fir group (FIRS 1), western white pine (PIMO 2, PIMO 3), and western hemlock (TSHE 2, TSHE 3, TSHE 4). These species' models are consisted with previous findings that crown injury and cambium kill are the most important variables to predicting tree mortality (Hood et al., 2010; Ganio and Progar, 2017). Bark beetle infestation status also played a large role in predictive accuracy for grand fir, the grand fir and white fir combined group (Firs), and western hemlock. Because cambium injury and beetle infestation require post-fire monitoring and, in the case of cambium injury, significant time to measure, we developed models without those variables where possible (ABAM 3, ABGR 4, PIMO 3, TSHE 4). The resulting equations relied on crown injury and bole scorch as the main factors.

FOFEM 5 is not adequate for predicting western redcedar or Alaska cedar mortality on an individual tree basis. There are no species-specific models available for either (Table 2). We did not have large enough or properly distributed samples to generate new mortality models or threshold guidelines. Although Alaska cedar is relatively uncommon in the Pacific Northwest, particularly in commercially managed forests, western redcedar is both widespread and valuable. Further research is needed to develop accurate models that predict the post-fire mortality of western redcedar.

The Scott guidelines yielded mixed results. They consistently overpredicted mortality for the fire-sensitive true firs, lodgepole pine, and Engelmann spruce, while they underpredicted mortality for more fire-resistant species, western larch and western white pine. The guidelines are unlikely to be acceptable for use in white fir, subalpine fir, grand fir, white pine, lodgepole pine, or Engelmann spruce, but may be satisfactory for western larch. Wagener's criteria generally performed better than the Scott guidelines, although white fir and sugar pine both had high FPRs and incense cedar had a high FNR (Table 4). Hood et al. (2010) found Wagener's criteria underpredicted mortality for these three species in Northern California, with high TNRs but TPRs below 65%. The data ranges in this study and Hood et al. (2010) are similar for many species, but this study includes a wider range of tree sizes, particularly smaller-diameter trees, which may explain the discrepancy between the two studies. Ambrosia beetle attack rates were lower and mountain pine beetle was not a factor in the California study. This highlights the impact that geographic region and range of data can have on predictive accuracy.

The new thresholds we developed consistently outperform the Scott guidelines and Wagener's criteria in overall classification accuracy and frequently in both mortality prediction and survival prediction. We attempted to balance classification so that the guidelines roughly predicted mortality and survival equally while maximizing %C, but some sets were still skewed. For instance, the western hemlock guidelines overpredict mortality with a FPR of 48%, but a FNR of just 7%. This should be taken into consideration when utilizing these guidelines. These new thresholds need further validation to determine how well they will extrapolate to other regions and fires.

4. Conclusions

This study validates existing post-fire mortality and thresholds for 14 conifers. 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. Models that included a beetle component or a cambium injury term (e.g., CKR, BSH) were consistently more accurate than those without. Though many management decisions must be made in planning stages before a fire, this increase in accuracy should be considered when deciding which mortality prediction method to use for post-fire activities. This is in agreement with other findings (Sieg et al., 2006; Hood et al., 2010; Ganio and Progar, 2017). Logistic regressions may be particularly helpful in meeting management objectives when used pre-fire for prescribed fire planning and long-term successional modeling (Keane et al., 2011). However, thresholds often exist that are simpler and easier to apply to individual trees (Fowler et al., 2010). The available Scott guidelines and Wagener's criteria are not generally adequate in classifying mortality and survival in Washington and Oregon for these species. We therefore developed thresholds that can be used to aid in ground assessments of individual tree mortality after fire.

Fire is a driving force in the North American landscape and predicting post-fire tree mortality is vital to land management. However, most mortality models were developed for Douglas-fir and ponderosa pine, and many are based on datasets from California. These models are not necessarily applicable to other regions, and many species lack empirically based mortality models. Additionally, models made for a particular species may not adequately classify mortality in all geographic regions. We developed new models for many tree species that previously lacked mortality equations, but there were too few observations to fit models for western redcedar or Alaska yellow cedar. Burn season and fire types have been shown to affect tree mortality (Harrington, 1987, 1993). Including burn season did not improve model performance, though this may be due to a limited range of burn seasons in our dataset. We could not compare potential differences between fire type (e.g. prescribed or wildfire), as all our data came from wildfires. Further work is needed for these factors and for the many other species lacking robust validation. 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 to aid in fire and forest management.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.foreco.2017.05.038.

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