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ARTICLE

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Predictive accuracy of post-fire conifer death declines over time in models based on crown and bole injury

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Abstract

A key uncertainty of empirical models of post-fire tree mortality is understanding the drivers of elevated post-fire mortality several years following fire, known as delayed mortality. Delayed mortality can represent a substantial fraction of mortality, particularly for large trees that are a conservation focus in western US coniferous forests. Current post-fire tree mortality models have undergone limited evaluation of how injury level and time since fire interact to influence model accuracy and predictor variable importance. Less severe injuries potentially serve as an indicator for vulnerability to additional stressors such as bark beetle attack or moisture stress. We used a collection of 164,293 individual tree records to examine post-fire tree mortality in eight western USA conifers: *Abies concolor*, *Abies grandis*, *Calocedrus decurrens*, *Larix occidentalis*, *Pinus contorta*, *Pinus lambertiana*, *Pinus ponderosa*, and *Pseudotsuga menziesii*. We evaluated the importance of fire injury predictors on discriminating between surviving trees versus immediate and delayed post-fire mortality. We fit balanced random forest models for each species using cumulative tree mortality from 1 to 5-years post-fire. We compared these results to multi-class random forest models using first-year mortality, 2–5-year mortality, and survival 5-years post-fire as a response variable. Crown volume scorched, diameter at breast height, and relative bark char height, were used as predictor variables. The cumulative mortality models all predicted trees that died within 1-year of fire with high accuracy but failed to predict 2–5-year mortality. The multi-class models were an improvement but had lower accuracy for predicting 2–5-year mortality. Multi-class model accuracies ranged from 85% to 95% across all species for predicting 1-year post-fire mortality, 42%–71% for predicting 2–5-year mortality, and 64%–85% for predicting trees that lived past 5-years. Our study highlights the differences in tree species tolerance to fire injury and suggests that including second-order predictors such as beetle attack or climatic water stress before and after fire will be critical to improve accuracy and better understand the mechanisms and patterns of fire-caused tree death. Random forest models have potential for management applications such as post-fire harvesting and simulating future stand dynamics.

KEYWORDS
Abies, *Calocedrus*, crown scorch, delayed mortality, fire-caused injury, FTM database, *Larix*, *Pinus*, post-fire tree mortality, *Pseudotsuga*, random forest, wildland fire

INTRODUCTION

Wildland fires are widely predicted to increase in their frequency, extent, and severity under future climate scenarios (Gao et al., 2021). Tree mortality from wildland fires affects post-fire forest structure and composition (Bond et al., 2005; Hagan et al., 2015), watershed function (Hallema et al., 2017), wildlife habitat (Van Lear & Harlow, 2002), and carbon storage (Loehman et al., 2014), among other ecosystem services (Vukomanovic & Steelman, 2019). Accurate modeling of post-fire tree mortality is important for determining where and when to do post-fire harvest, post-fire tree planting, and where to prioritize future silviculture and prescribed fire treatments (Hood et al., 2018). Tree mortality models are also useful for simulating future stand and landscape level dynamics over longer time frames to understand the impacts of fire on landscape heterogeneity and resilience to fires (Larson et al., 2022).

Both empirical and mechanistic process-based models have been proposed for describing post-fire tree mortality, the former are used primarily for prediction and probability of mortality while the latter are used to identify the causal mechanisms that result in mortality (Michaletz & Johnson, 2007; O'Brien et al., 2018). However, our current understanding of the complex processes involved in tree mortality is rudimentary (Das et al., 2016; Hood et al., 2018; Trugman et al., 2021; Waring, 1987). This has led to the nearly exclusive use of empirical models in applications such as the First Order Fire Effects Model (FOFEM; Lutes, 2020) and the Fire and Fuels Extension to the Forest Vegetation Simulator (FFE-FVS; Reinhardt & Crookston, 2003) when predicting tree mortality for management purposes.

For empirical models of individual tree mortality, a binary tree status (live or dead) is modeled as a function of several predictors. These predictors commonly include some measure of fire injury, tree attributes such as height and diameter, and sometimes include measures of fire behavior, fuel consumption or bark beetle presence (Hood et al., 2010; Peterson & Ryan, 1986; Ryan & Reinhardt, 1988; Thonicke et al., 2010; Woolley et al., 2012). Models are most often fit using logistic regression (Cansler, Hood, van Mantgem, & Varner, 2020; Woolley et al., 2012), although generalized linear models, structural equation modeling, and machine learning methods such as random forest have been shown to be effective as well (Furniss et al., 2022; Menges & Deyrup, 2001; Shearman et al., 2019; Youngblood et al., 2009).

Fire-caused crown injury is consistently the best predictor of post-fire tree mortality (Cansler, Hood, van Mantgem, & Varner, 2020; Sieg et al., 2006; Woolley et al., 2012). Crown scorch can be a result of tissue necrosis by direct application of lethal heat energy doses, as well as xylem dysfunction by either heat-induced embolisms or deformation of xylem (Varner et al., 2021). Crown consumption occurs when a tree's foliage, buds, and fine branches combust from exposure of more extreme thermal environments (Varner et al., 2021). Several previous studies have suggested that some species can survive relatively high levels of crown scorch up to a certain threshold value—a "crown scorch threshold"—where the probability of mortality increases dramatically (Fowler et al., 2010; Harrington, 1987; Lynch, 1959; McHugh et al., 2003; Peterson & Arbaugh, 1986). For example, Fowler et al. (2010) found that the mortality rate significantly increased in ponderosa pine (*Pinus ponderosa*) with greater than 88% of their crown volume scorched and no crown consumption. Crown scorch reduces photosynthetic leaf area, causing short-term stress and potential reductions in radial growth and possibly mortality (Varner et al., 2021; Weise et al., 2016). The loss of buds from crown consumption is linked to higher tree mortality (Hood et al., 2018) and thus even trees that have high crown scorch thresholds may be sensitive to minimal crown consumption (Fowler et al., 2010; Varner et al., 2007, 2021). Most studies that report crown scorch thresholds have focused on the widespread western North American conifers ponderosa pine and Douglas-fir (*Pseudotsuga menziesii*), although Grayson et al. (2017) reported crown scorch and cambium kill thresholds for nine additional conifers. Differences in scorch thresholds are likely due to interspecific differences in susceptibility of injury to different tissues (e.g., scorch of foliage does not result in bud death in all species), and interspecific differences in the ability to recover after scorch due to ability to resorb nutrients, or resprout from epicormic buds (Varner et al., 2021).

Bole injury is another common predictor variable used in post-fire tree mortality models, acting as an indicator of cambial injury (Beverly & Martell, 2003; Hood et al., 2008; Thies et al., 2006). Metrics of bole injury include the height of charring, proportion of circumference/height charred, and measures of depth or severity of charring (Hood et al., 2018; Nemens et al., 2019). The use of bark charring as a metric of injury has received some criticism, since this external measure fails to encompass underlying injury to vascular cambia, especially for thick barked species (Hood et al., 2018) and more often, charring is simply an indicator of flaming zone heating and fire spread direction. Bark char also cannot be estimated from any fire behavior variable such as flame length or fireline intensity, making it impossible to predict the bark char severity or presence/absence in advance of a fire. Recent work on bark char reflectance offers some promise for a better quantitative metric of bole injury (Belcher et al., 2021), but has yet to be validated on multiple species and remains untested in post-fire surveys.

While crown and bole predictor variables are measurements of fire-caused injury, tree defenses are captured by predictors such as bark thickness. Bark provides an insulative layer that protects the underlying cambium from lethal temperatures, with the degree of protection scaling positively with the square of its thickness (Barlow et al., 2003; Bauer et al., 2010; Hare, 1965; van Mantgem & Schwartz, 2003; Vines, 1968). Bark thickness and thermal properties vary across species and stem size, with species in frequent-fire ecosystems generally developing thicker bark than those where fire is less frequent (Pellegrini et al., 2017). In most models of post-fire tree mortality where bark thickness is included as a predictor, bark thickness is often estimated using allometric relationships between stem diameter and bark thickness. One criticism of using allometric equations (e.g., those used in FOFEM and FVS-FFE) to estimate bark thickness is that they generally assume a linear relationship with stem diameter, which neither matches theoretical concepts for allocations between defense and growth (Jackson et al., 1999), nor observations which generally show more rapid increase in single bark thickness in smaller trees than larger trees of the same species (Pausas, 2015).

The response variable (tree status) in empirical models is based on the condition of a tree in a single point in time, often assessed anywhere from one to five-years post-fire (Woolley et al., 2012). This timeframe can blur the line between first-order fire effects, those due to immediate damage to tree meristems and/or vascular systems, and second-order fire effects, those associated with subsequent factors such as post-fire drought or beetle attack (Agee, 2003; Hood et al., 2018; Reinhardt & Dickinson, 2010). For example, most fire-caused mortality occurs in the first 3 years (Agee, 2003; Harrington, 1993; Hood et al., 2010; Ryan & Reinhardt, 1988; Wagener, 1961), but tree death above "background" mortality relative to unburned stands can occur well past this timeframe (Agee, 2003; Collins et al., 2014; Ryan et al., 1988; van Mantgem et al., 2011). This delayed mortality may be particularly important for trees with less severe injuries (Knapp et al., 2021; Maringer et al., 2021; Thies et al., 2006; van Mantgem et al., 2011). In many circumstances, only one post-fire census for mortality is taken due to limitations of time or resources, so tree status is often the cumulative mortality that occurred from immediately after the fire until the point in time where the tree status was assessed. Thus the precise year of mortality is not known. Despite the fact that empirical models seem to work well at predicting mortality (Cansler, Hood, van Mantgem, & Varner, 2020), they are not designed to provide information as to when the tree will die other than some time before the post-fire year which was used to fit the model. Similarly, these models can only provide information on the importance of predictor variables for the cumulative timeframe that was used to fit the models. It is unclear how time since fire affects both the accuracy of empirical models and the importance of predictor variables.

Although individual tree mortality following fire is commonly described in terms of crown scorch, bark char and bark thickness, the importance of these factors may change with increasing time since the fire and their relative importance may differ between species. Mortality that occurs within the first year following fire may be best predicted by first-order effects (crown scorch, bark char), while second-order effects such as drought or insect and pathogen activity may become more important for predicting delayed mortality. For example, Maringer et al. (2021) found that the importance of fungal infestation as a predictor of mortality increased over time for European beech (*Fagus sylvatica* L.) following low- to moderate-severity fire. Nesmith et al. (2015) found that by 1-year post-fire indices of tree vigor were not supported in empirical models mortality for sugar pine (*Pinus lambertiana* Douglas), but were supported at 5-year post-fire when observations of delayed mortality were included. As a result, empirical models based solely on a single time since fire may be biased toward either first- or second-order effects. Species specific differences in defenses, resilience and resistance to different types of injuries, and whether associated bark beetle species typically cause mortality (i.e., are "primary beetles") will interact with the temporal importance of different injuries to influence mortality over time.

Understanding the factors important to post-fire tree mortality requires large amounts of data across multiple fires. We analyzed data from the Fire and Tree Mortality

(FTM) Database (Cansler, Hood, Varner, van Mantgem, Agne, Andrus, Ayres, Ayres, Bakker, Battaglia, et al., 2020; Cansler, Hood, Varner, van Mantgem, Agne, Andrus, Ayres, Ayres, Bakker, Battaglia, Bentz, et al., 2020), a collection of 164,293 individual tree records including measures of fire injury, tree diameter, and status (live/dead). The data include 142 species from 409 fires spanning 11 western US states from 1981 to 2016 (Cansler, Hood, Varner, van Mantgem, Agne, Andrus, Ayres, Ayres, Bakker, Battaglia, et al., 2020; Cansler, Hood, Varner, van Mantgem, Agne, Andrus, Ayres, Ayres, Bakker, Battaglia, Bentz, et al., 2020, Figure 1). The objectives of this study were: (1) to evaluate models using fire injury predictors over different years of cumulative post-fire mortality and compare them to models that specify when trees died; (2) to determine if the importance of predictor variables differ depending on when mortality occurs; and (3) to compare species for their relative sensitivity to crown and bole injuries with increasing time since fire. We hypothesized that accuracy would decrease over time since fire due to mortality from second-order fire effects. We also hypothesized that trees with higher levels of injury would have higher probability of mortality in the first year post-fire. This research focused on eight western USA tree species with sufficient data (555–19,850 live trees and 155–8128 dead trees), but this model could have much wider applicability as data are added to the FTM database.

METHODS

We selected the species with the most records in the FTM database across 5 years of post-fire observations.

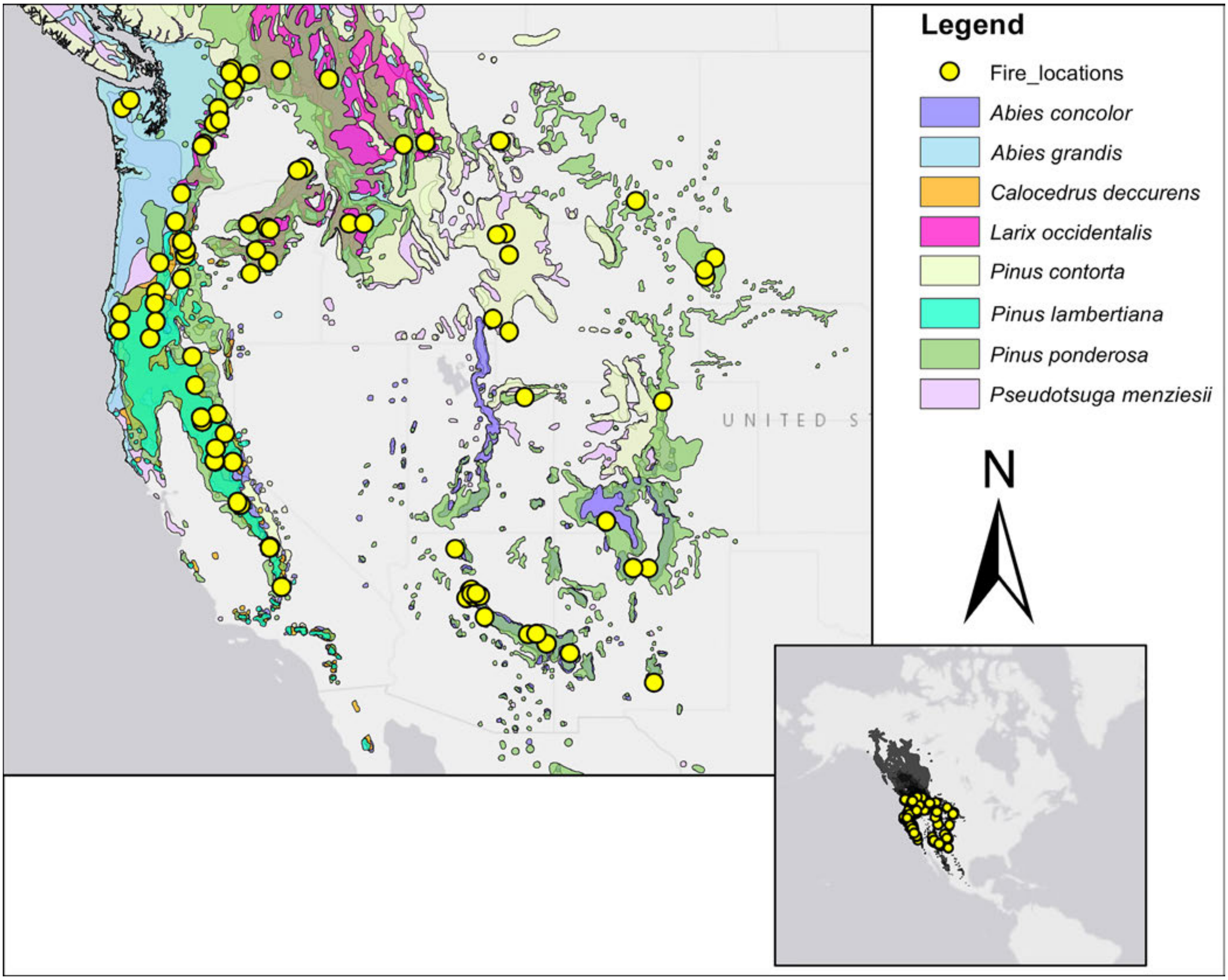

FIGURE 1 Geographic extents of the eight species in the study based on Little Jr. (1971). Points represent locations of fires where post-fire tree mortality data were collected.

These species include *Abies concolor* ($n = 17{,}236$ observations, 6181 trees), *Abies grandis* ($n = 3989$ observations, 1550 trees), *Calocedrus decurrens* ($n = 7091$ observations, 2194 trees), *Larix occidentalis* ($n = 3505$ observations, 909 trees), *Pinus contorta* ($n = 10{,}058$ observations, 4613 trees), *P. lambertiana* ($n = 4277$ observations, 1332 trees), *P. ponderosa* ($n = 68{,}940$ observations, 27,978 trees), and *Pseudotsuga menziesii* ($n = 40{,}270$ observations, 12,828 trees). Observations were made across all species ranges (Figure 1). These conifers dominate or can be major components of many fire-prone savannas, woodlands, and forests in western North America (Eyre, 1980). All trees assessed in this study were sampled for tree injury and diameter at breast height (DBH) within one-year post-fire and then assessed over time for mortality at various years (up to 5-years) depending on the original study protocols. Only trees with a DBH of at least 10 cm were used in the analyses.

To evaluate cumulative post-fire mortality models, we fitted a balanced random forest model using a binary tree status (live/dead) as the response variable for each species and each year of mortality observations. Random forest is a machine learning algorithm in which ensembles of classification trees are fit to random sets of observations and predictors in the training data (Breiman, 2001). For each classification tree, the observations not selected for fitting (i.e., "out-of-bag") are used to assess error. The randomized subsets of the data reduce bias in the models and prevents overfitting. However, like logistic regression, random forests models can be biased when classes in the training data are imbalanced (e.g., more dead trees than live trees). Shearman et al. (2019) showed that balanced random forest models, where equal observations of each class are used in training, improves mortality prediction and alleviates bias in the models.

To accommodate the different number of observations for each species and in each year, we balanced both live and dead trees to 20% of the total dead trees or live trees (whichever was lower) for each species in each year. For each model, 10,000 classification trees were grown. FTM attributes "CVS_percent" (percentage of the crown volume scorched or consumed by fire), "DBH_cm" (DBH in cm), and "BCH_percent" (percentage of total tree height blackened or charred), were used as predictor variables. Only complete observations where all predictor variables were measured were used to avoid missing data.

To assess model accuracy, we used five-fold cross validation to evaluate the model accuracy by splitting the data for each tree species randomly into five subsets, fitting new random forest models to four of the five subsets and testing accuracy including sensitivity (i.e., correctly predicted mortality), specificity (i.e., correctly predicted survival), and total accuracy on the remaining subset (see Cansler, Hood, van Mantgem, & Varner, 2020 for description of model performance evaluations). Classifications were made based on the majority vote of trees in the random forest (i.e., $P_{\text{mort}} > 0.5$ were classified as dead). Because models were fit using cumulative mortality, we assessed the error of the models to see if they were sensitive to when the mortality occurred. Not all trees in the FTM database had mortality observations in every year, so we did not have the exact mortality year for many trees. Most datasets had observations in post-fire year-1 and many had at least one additional observation in years 2–5. Therefore, to increase our sample size over all species, we grouped dead trees into two categories: dead in post-fire year-1 and dead sometime in post-fire years 2–5. We then compared the percentage of dead trees incorrectly predicted to be alive (i.e., false negatives) between both categories for all models using the formula:

$$\frac{\text{FN}}{\text{TP}+\text{FN}} \times 100,$$

where FN is the number of false negative predictions and TP is the number of true positive predictions (dead trees). A paired sample t-test in which predictions from each fold for each species was paired was used to compare the percent of false negatives between tree mortality in year-1 and mortality in years 2–5. False negatives were used to compare models because we wanted to see where the models failed to predict dead trees. Model performance statistics that assess the performance of predicting live trees such as specificity or total accuracy could lead to incorrect assessments in this analysis. For example, a tree that died in post-fire year-3 could be predicted to be alive by models fit to data from any previous years (i.e., years 1 and 2).

To see how the importance value of predictor variables and predicted tree mortality changes with tree species and with post-fire year, we fit a balanced multi-class random forest model using three classes (dead in post-fire year-1, dead in post-fire years 2–5, and live at least 5-years) as the response variable. The model parameters were the same as in the cumulative models listed above. Distributions of predictor variables are provided in Appendix S1: Figure S1. Classifications, again, were made based on the majority vote of trees in the random forest, however because there were three response classes the predicted class could be lower than 0.5 (e.g., a tree with $P_{\text{mortality year1}} = 0.4$, $P_{\text{mortality year2–5}} = 0.3$, and $P_{\text{Live}} = 0.3$ would be classified as dead in year-1). Variable importance of a predictor in random forest classification models can be calculated as the mean decrease in accuracy of predicting out-of-bag data when the variable is randomly permuted versus including the actual predictor values (Breiman, 2001). These importance values were calculated for each class of the response variable to see which predictors were important in predicting dead trees in year-1, dead trees in years 2–5, and live trees over 5-years post-fire. Partial dependence plots of pairs of predictors (crown scorch, bark char, and DBH) were estimated for each species. These plots show the marginal change in probability of mortality with changes in two predictor variables accounting for the average effect of the third variable in the model.

All analyses were performed in *R* version 4.0.3 (R Core Team, 2019). Cross validation subsets were made using the *Caret* package (Kuhn, 2020), models were fit using the *randomForest* package (Liaw & Wiener, 2002), and partial dependence plots were created with the *pdp* package (Greenwell, 2017).

RESULTS

For the eight species we evaluated in the FTM database, most studies recorded observations of tree status within the first 5 years post-fire, with year 1 having the most fires with observations ($n = 258$ fires). Observations per fire declined every year post-fire with 191 fires in year 2, 150 fires in year 3, 93 fires in year 4, and 59 fires in year 5 (Appendix S1: Table S1). *Pinus ponderosa* had the most observations with 19,302 in post-fire year-1, while the other species had substantially fewer observations in post-fire year-1 (10,085 for *P. menziesii*; 3535 for *A. concolor*; 3283 for *P. contorta*; 1251 for *C. decurrens*; 810 for *P. lambertiana*, 996 for *A. grandis*, and 790 for *L. occidentalis*; Appendix S1: Table S1). Mortality ranged from 28.3% to 69.5% across the *A. concolor* datasets, 20.1%–59.7% across *A. grandis*, 39.4%–72.7% across *C. decurrens*, 8.0%–18.0% across *L. occidentalis*, 48.9%–82.8% across *P. contorta*, 33.0%–58.2% across *P. lambertiana*, 16.5%–30.6% across *P. ponderosa*, and 16.8%–37.9% across *P. menziesii* (Appendix S1: Table S1).

Specificity, sensitivity, and total accuracy was high for all cumulative models (0.73–0.99, 0.50–0.96, and 0.55–0.98 respectively over all species and time since fire), and was higher for specificity (predicting live trees). All measures were highest in the 1-year post-fire models for all species and generally decreased in all later models (Table 1). Despite having high specificity, sensitivity, and total accuracy, false negative error greatly differed on predictions for trees that died 1-year post-fire compared to those that died 2–5 years post-fire (Figure 2). All models had low false negative error for predicting 1-year post-fire mortality, but the 2–5-year models had significantly higher error in predicting 2–5-year post-fire mortality ($p \leq 0.05$ for all tests, Appendix S1: Table S2). False negative error was 48.2%–59.0% higher across *A. concolor* 2–5-year post-fire models, 31.8%–52.6% higher across *A. grandis* models, 48.8%–82.9% higher across *C. decurrens* models, 26.6%–51.9% higher across *L. occidentalis* models, 21.1%–60.7%, higher across *P. contorta* models, 47.0%–56.1% higher across *P. lambertiana* models, 35.2%–49.3% higher across *P. ponderosa* models, and 15.3%–44.0% higher across *P. menziesii* models compared to the 1-year post-fire models (Figure 2).

For trees in the FTM database where the approximate time of mortality or survival up to 5-years was known, mean crown volume scorched and relative bark char height were highest in trees that died within one-year post-fire and lowest in trees that survived at least 5-years for all species (Table 2). The range for these injury variables were similar (0–100) for each response class for all species with the exception of *A. concolor*, *A. grandis*, and *L. occidentalis* which had lower maximum percent bark height charred in trees that died in years 2–5 and trees that lived for more than 5 years (Table 2). *Pinus contorta* also had a lower maximum bark char for trees that lived more than 5-years (56%). Larger trees of all species survived longer than small diameter stems.

Accuracy for the multi-class random forest models also differed between classes and species. Again, all models predicted trees that died 1-year post-fire with high accuracy (85.4%–95.1%) on average over all folds across all species (Figure 3). Average accuracy for predicting mortality 2–5-years post-fire ranged from 42.1 to 70.5 and accuracy for predicting trees that lived up to 5-years post-fire ranged from 64.1% to 84.5% (Figure 3).

Predictor variable importance differed between species and between response class within species (Figure 4). Crown volume scorch had the highest variable importance for all classes in *A. concolor*, *C. decurrens*, *P. lambertiana*, *P. ponderosa*, and *P. menziesii*. For these species, bark char and DBH have lower variable importance for post-fire year-1 and years 2–5, and are slightly higher in importance for live trees over 5-years, with DBH having approximately the same importance value as crown scorch in *P. lambertiana*. Crown scorch and DBH predictor importance were also high in predicting live trees over 5-years post-fire for *C. decurrens*, but were lower for predicting both classes of dead trees. For *A. grandis*, crown scorch had the highest variable importance for predicting dead year-1 trees, whereas all three variables had similar but lower importance for mortality in years 2–5, and bark char and crown scorch had higher importance for predicting live trees over 5-years. Crown scorch and DBH were

TABLE 1 Cross validated results of random forest models for predicting cumulative mortality from 1 to 5 years post-fire.

Species	Post-fire year	Specificity	sdSpec	Sensitivity	sdSens	Total	sdTotal
Abies concolor	1	0.98	0.00	0.92	0.02	0.97	0.01
	2	0.91	0.03	0.78	0.03	0.85	0.02
	3	0.91	0.02	0.76	0.02	0.83	0.01
	4	0.87	0.03	0.72	0.05	0.78	0.02
	5	0.86	0.04	0.69	0.04	0.74	0.02
Abies grandis	1	0.95	0.01	0.92	0.05	0.94	0.01
	2	0.87	0.03	0.70	0.06	0.80	0.03
	3	0.81	0.06	0.65	0.08	0.71	0.03
	4	0.73	0.08	0.64	0.04	0.68	0.01
	5	0.82	0.28	0.68	0.12	0.75	0.17
Calocedrus decurrens	1	0.97	0.02	0.95	0.02	0.96	0.02
	2	0.95	0.03	0.96	0.03	0.95	0.02
	3	0.96	0.02	0.93	0.03	0.94	0.03
	4	0.96	0.04	0.94	0.01	0.95	0.02
	5	0.96	0.04	0.96	0.04	0.96	0.02
Larix occidentalis	1	0.88	0.05	0.86	0.09	0.87	0.05
	2	0.85	0.04	0.72	0.09	0.84	0.03
	3	0.85	0.02	0.69	0.06	0.83	0.03
	4	0.79	0.04	0.64	0.11	0.76	0.02
	5	0.79	0.10	0.66	0.12	0.77	0.09
Pinus contorta	1	0.96	0.01	0.92	0.01	0.94	0.01
	2	0.93	0.02	0.86	0.01	0.89	0.01
	3	0.91	0.02	0.80	0.03	0.84	0.02
	4	0.82	0.05	0.78	0.04	0.80	0.04
	5	0.81	0.23	0.50	0.10	0.55	0.09
Pinus lambertiana	1	0.98	0.01	0.94	0.02	0.96	0.01
	2	0.93	0.03	0.81	0.06	0.87	0.04
	3	0.88	0.04	0.78	0.04	0.82	0.03
	4	0.91	0.05	0.77	0.03	0.83	0.02
	5	0.93	0.05	0.78	0.07	0.84	0.05
Pinus ponderosa	1	0.99	0.00	0.93	0.01	0.98	0.00
	2	0.94	0.00	0.85	0.02	0.92	0.01
	3	0.91	0.01	0.79	0.00	0.88	0.00
	4	0.81	0.02	0.67	0.02	0.78	0.01
	5	0.78	0.02	0.63	0.08	0.75	0.01
Pseudotsuga menziesii	1	0.99	0.00	0.93	0.01	0.97	0.00
	2	0.94	0.00	0.86	0.02	0.92	0.00
	3	0.93	0.01	0.82	0.01	0.89	0.01
	4	0.82	0.02	0.69	0.03	0.79	0.02
	5	0.79	0.01	0.69	0.02	0.77	0.01

Note: Specificity is the average rate of predicting live trees across the five-fold cross validation datasets. Sensitivity is the average rate of predicting dead trees. sdSpec, sdSens, and sdTotal are the standard deviations of the respective means.

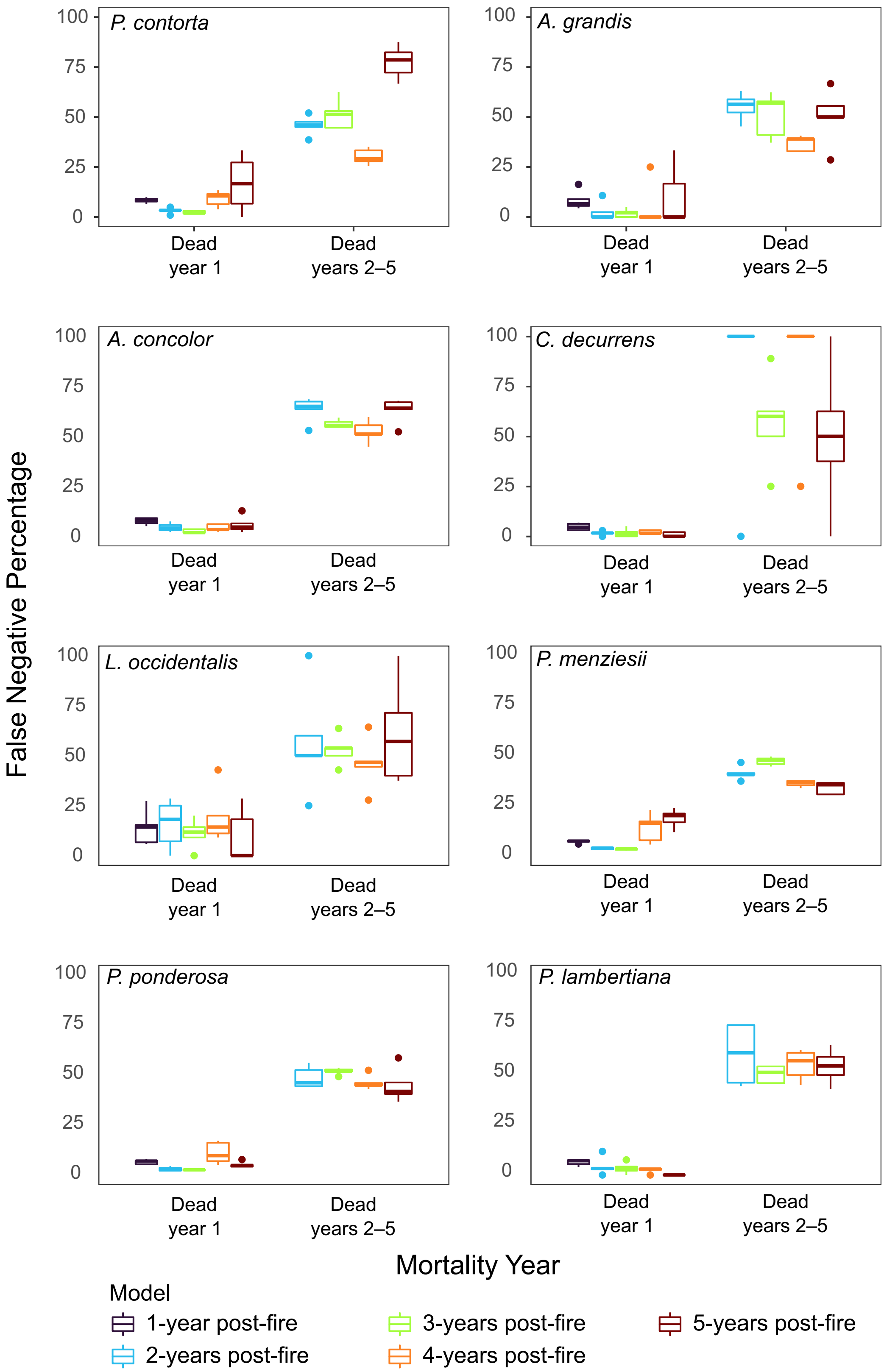

FIGURE 2 Percentage of false negative predictions (dead trees incorrectly predicted to be alive) of cumulative random forest models for tree mortality that occurred one and two-5 years post-fire. Models were fit using a balanced random forest with status (live/dead) as a response and crown volume scorched (%), diameter at breast height (cm), and bark char (% of total height) as predictor variables. A separate model was fit for each post-fire year and species. Boxplots show the results of five-fold cross validation for each model. Horizontal bar in each boxplot represents the median. Boxes represent the interquartile range (IQR) and whiskers extend to the furthest point up to 1.5 × IQR.

TABLE 2 Status of trees included in multi-class random forest models.

Species	Response class	*N*	Mean CVS (%)	Minimum/maximum CVS (%)	Mean BCH (%)	Minimum/maximum BCH (%)	Mean DBH (cm)	Minimum/maximum DBH (cm)
Abies concolor	Dead year 1	1002	96.2	0/100	36.9	0/100	23.3	10.0/104.5
	Dead years 2–5	788	50.7	0/100	19.3	0/93	39.4	10.0/218.4
	Live >5 years	433	28.2	0/100	12.1	0/53	40.6	10.0/108.7
Abies grandis	Dead year 1	200	96.9	10/100	54.5	1/100	26.8	10.4/85.3
	Dead years 2–5	461	38.3	0/100	14.9	0/83	47.5	10.2/106.7
	Live >5 years	60	10.2	0/90	3.8	0/28	33.3	10.2/85.6
Calocedrus decurrens	Dead year 1	493	98.3	0/100	58.5	0/100	20.1	10.0/111.0
	Dead years 2–5	47	64.1	0/100	28.4	0/86	33.3	10.0/132.8
	Live >5 years	96	14.7	0/100	24.0	0/100	51.8	14.5/149.9
Larix occidentalis	Dead year 1	63	74.3	0/100	34.3	0/100	23.4	11.4/73.5
	Dead years 2–5	83	28.8	0/100	19.8	0/66	39.4	14.5/119.4
	Live >5 years	334	14.7	0/100	10.3	0/84	37.9	14.0/111.3
Pinus contorta	Dead year 1	1605	83.0	0/100	55.2	0/100	19.7	10.0/102.9
	Dead years 2–5	606	27.3	0/100	8.4	0/100	27.6	10.2/63.8
	Live >5 years	29	8.7	0/50	8.0	0/56	26.9	16.8/50.0
Pinus lambertiana	Dead year 1	267	96.5	0/100	43.4	0/100	21.8	10.0/130.5
	Dead years 2–5	191	56.3	0/100	21.9	0/73	52.5	10.2/199.3
	Live >5 years	155	29.0	0/95	15.3	0/76	71.0	17.8/148.1
Pinus ponderosa	Dead year 1	3185	96.5	0/100	69.9	0/100	22.9	10.0/175.0
	Dead years 2–5	2157	56.3	0/100	32.8	0/100	34.0	10.1/132.6
	Live >5 years	3567	29.0	0/100	18.6	0/100	43.0	10.0/125.0
Pseudotsuga menziesii	Dead year 1	2439	95.9	0/100	60.6	0/100	29.9	10.0/126.2
	Dead years 2–5	1439	56.3	0/100	23.6	0/100	43.0	10.2/201.2
	Live >5 years	3587	15.5	0/100	14.0	0/84	53.7	10.0/210.8

Abbreviations: BCH, percent of total height charred; CVS, percent of crown volume scorched; DBH, diameter at breast height.

relatively high in predicting *L. occidentalis* trees that died in year-1, while all three predictors were similarly important for the other classes. Finally, for *P. contorta*, all crown scorch and bark char height were highest in predicting live trees and lowest for predicting dead year-1 trees.

The partial dependence plots show stark differences among species in the level of injuries in which the models predict mortality (Figures 5–7). The higher opacity of colors in these figures indicate areas of higher confidence (i.e., higher probability) in predictions. Models for all species predicted mortality within 1-year post-fire for trees with 100% crown scorch, but the probability decreased with increasing DBH (Figure 5). Mortality in years 2–5 was predicted in general for trees with moderate scorch and small diameters for most species but was highly variable between species. Similarly, trees predicted to live past 5-years were at the larger diameter ranges and had lower levels of crown damage, except for *P. contorta* and *A. concolor*, where diameter was not very predictive of survival. The partial dependence plots of crown volume scorched and percent of bark height charred indicate that trees with low levels of both of these injuries were predicted to live past 5-years, while high levels of crown scorch and a combined effect of crown scorch and bark char were predicted to be dead 1-year and 2–5 years respectively (Figure 6). The level of injury was again variable between species, with *P. contorta* having a clear threshold with those over approximately 30% bark charred predicted to die within 1-year post-fire (Figure 6). The partial dependence of bark char and diameter tended to have lower probabilities for all predicted classes, but the trend of smaller trees with higher bark char dying earlier was consistent with the previous partial dependence plots (Figure 7).

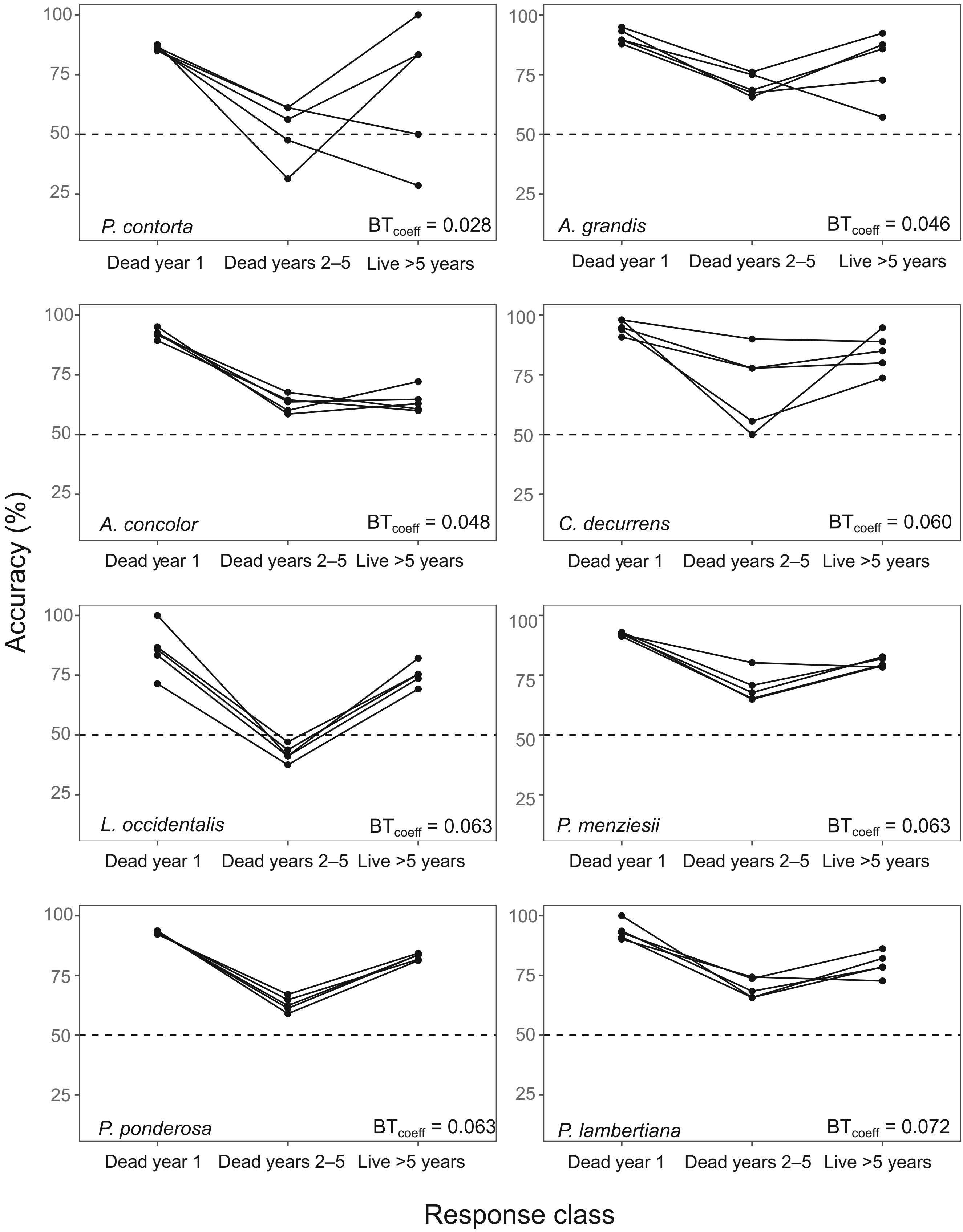

FIGURE 3 Accuracy of multiclass balanced random forest models for predicting post-fire tree mortality. Accuracy is the percent of correct predictions using five-fold cross validation. Lines connect predictions from each of the five fitted models in the cross validation. Dashed line indicates 50% accuracy. BT_{coeff} is the bark thickness coefficient used in first order fire effects model (Lutes, 2020).

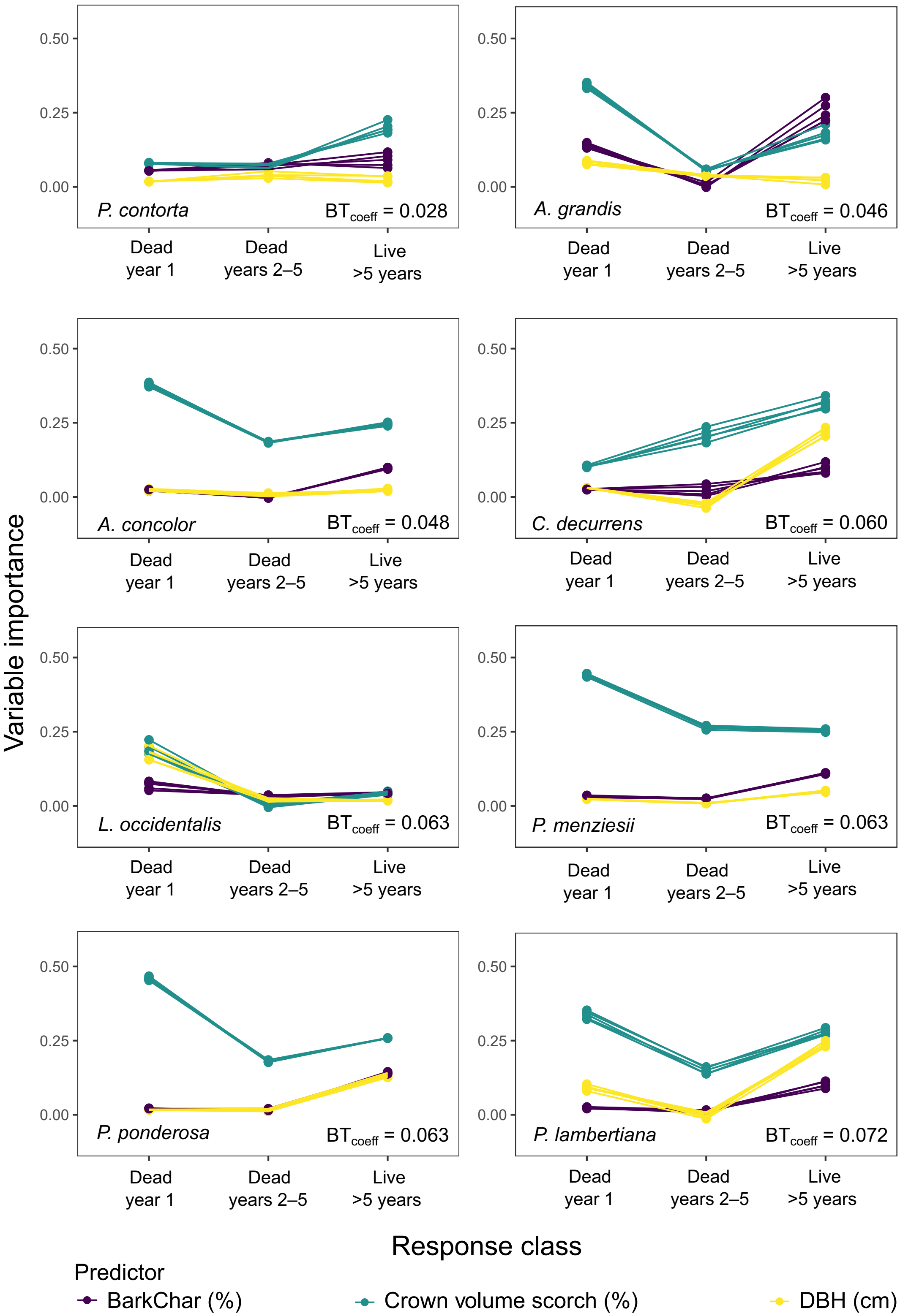

FIGURE 4 Variable importance for predictor variables in predicting post-fire tree mortality using balanced random forest models. Variable importance is the mean decrease in proportion of accurate predictions of out-of-bag data when the variable is randomly permuted versus including the actual predictor values. Models were assessed using five-fold cross validation. Lines connect the variable importance of each of the five fitted models in the cross validation for each predictor. BT_{coeff} is the bark thickness coefficient used in first order fire effects model (Lutes, 2020). DBH, diameter at breast-height.

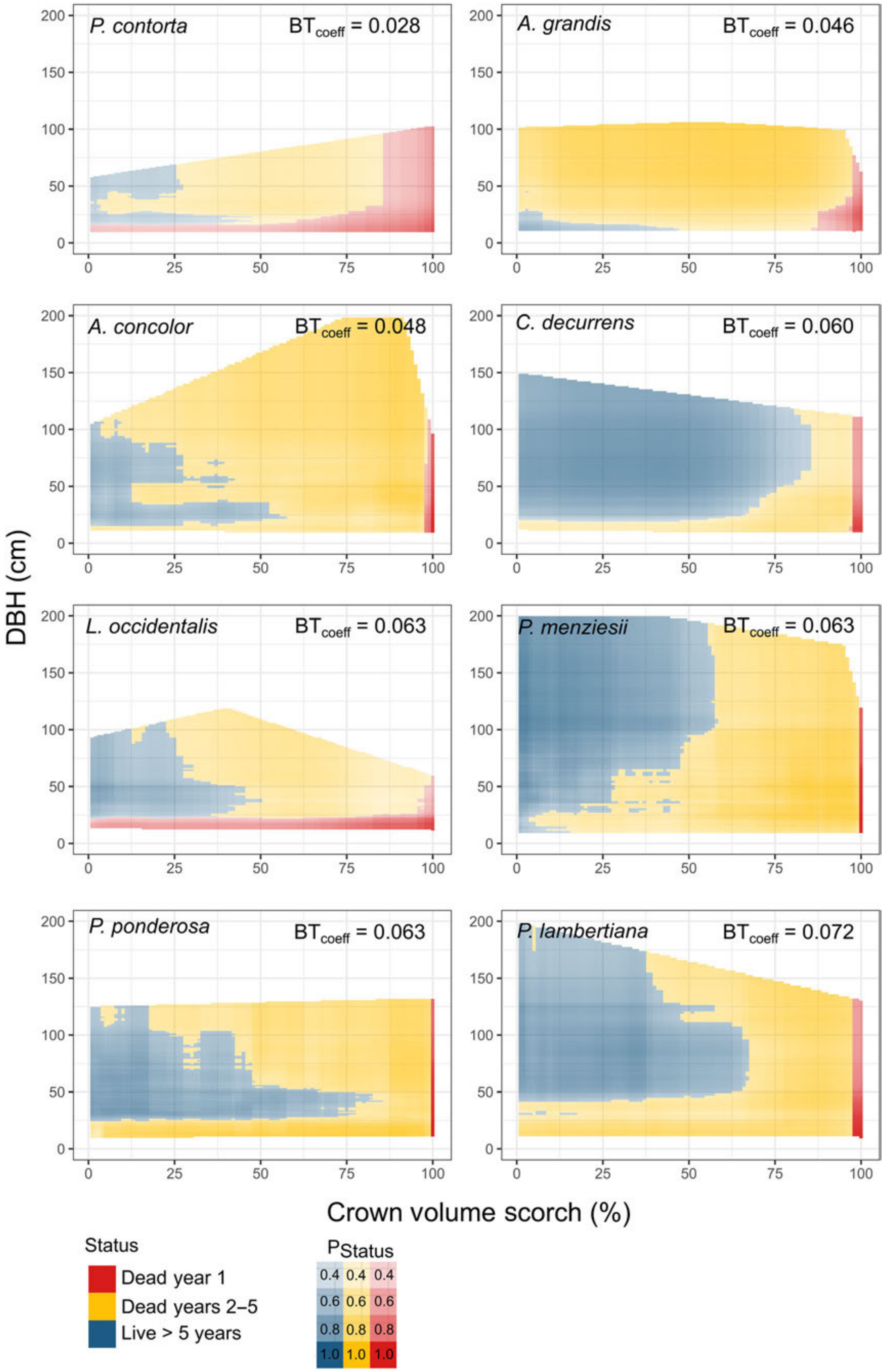

FIGURE 5 Legend on next page.

DISCUSSION

Our analysis demonstrates that models based on commonly used metrics of post-fire mortality capture tree death that occurs within 1-year post-fire, but model performance is poor for delayed mortality. When combining observations of immediate and delayed mortality, standard models based on crown scorch and bark char appear to perform well with high sensitivity, specificity, and total accuracy. This high performance is largely because of the high levels of mortality that occurs within the first year of a fire. For example, Hood et al. (2010) found that 70%–88% of mortality in five California conifers occurred within 2-years post-fire. Additionally, cumulative mortality models inherently cannot predict when the mortality occurs due to the limitations of a binary classification (live or dead) and no temporal information. Our study shows that incorporating as much temporal information as possible, such as our multi class random forest, is a better solution if managers want to be more informed on when mortality will occur. With the exceptions of *L. occidentalis* (which had the lowest mortality), *C. decurrens* (which was highly variable in the 2–5 year accuracy), and *P. contorta* (which was variable in all but first year mortality), the multi-class models performed well at predicting mortality and survival, albeit with consistent lower accuracy in predicting delayed mortality.

The greatest predictive performance for all of our multi-class models was in predicting first-year mortality. For all species in our dataset, trees with higher levels of fire injury died in the first-year post-fire. These trees likely experienced the most intense fire behavior and died from crown injuries or associated cambial injury (Hood et al., 2018; Varner et al., 2021). Models had fairly high specificity in predicting trees that lived past 5 years as well, selecting trees with little to no injury. Accuracy was generally lower or more variable in predicting mortality in years 2–5. The variability in accuracy could be due to a number of factors such as the limited knowledge of when the trees died within this period. For example, tree mortality in year-2 might be more accurately predicted by fire injury variables than tree mortality in year-5. More data with complete mortality observations in each post-fire year would help with studies on delayed mortality. Similarly, the drop in accuracy could indicate a shift over time from first-order fire effects to second-order fire effects (Kane et al., 2017; Nesmith et al., 2015). For example, Hood et al. (2010) found that including an indicator term of the red turpentine beetle (*Dendroctonus valens*) attack was significant in predicting 5-year post-fire tree mortality in *P. lambertiana*, *P. ponderosa*, and *P. jeffreyi*, and including a term for ambrosia beetle (*Trypodendron* and *Gnathotrichus* spp.) attack was significant for *A. concolor*. Drought or competitive stress before fire also have an effect on mortality, exacerbating the fire-caused stresses caused by crown and bole injury (Furniss et al., 2020, 2022; Hood et al., 2018; Nesmith et al., 2015; van Mantgem et al., 2013, 2018). Similarly, post-fire climate (duration and severity of drought) may be an important predictor in later post-fire years (Agee, 2003; Barker et al., 2022; Furniss et al., 2019; Knapp et al., 2021). Root injury from smoldering fires has also been suggested as mortality agents for trees with deep, dry, duff layers (Harrington, 2013; Hood, 2010; Ryan & Frandsen, 1991; Swezy & Agee, 1991; Varner et al., 2007). Local competition may be an important predictor as well (Das et al., 2011; Hood et al., 2018; van Mantgem et al., 2018). As post-fire datasets increase and the diversity of additional data is incorporated in the FTM database, we can improve on these models (Bonner et al., 2021).

The relationship of predictor variable importance to response class followed a similar pattern in *A. concolor*, *P. ponderosa*, and *P. menziesii*, with crown volume scorch having the highest variable importance for all classes. However, no clear pattern emerged across the other species. One reason for a lack of a clear pattern could be that predictor variable importance only provides information on the discriminatory ability of each variable and not on the positive or negative impact on the class label. For example, crown scorch is positively associated with first-year tree mortality but negatively associated with trees that live over 5-years (i.e., trees with low scorch are more likely to survive). Another possibility is that variable importance does not indicate interactions, so a variable with a low importance alone could have high discriminatory ability when included with another variable (Guyon & Elisseeff, 2003).

Bark char was moderately important for predicting trees of *P. contorta* and *A. grandis* that lived past 5 years. Unlike crown scorch, which is a direct measurement of fire injury, bark char is a potential indicator of fire damage to the cambium (Hood et al., 2018). Differences in

FIGURE 5 Partial dependence plots showing random forest model classification for given crown volume scorched and diameter at breast-height (DBH) accounting for the average effect of bark char. Colors represent the class with the highest predicted probability in the random forest model with more opaque colors having higher probability. BT_{coeff} is the bark thickness coefficient used in first order fire effects model (Lutes, 2020).

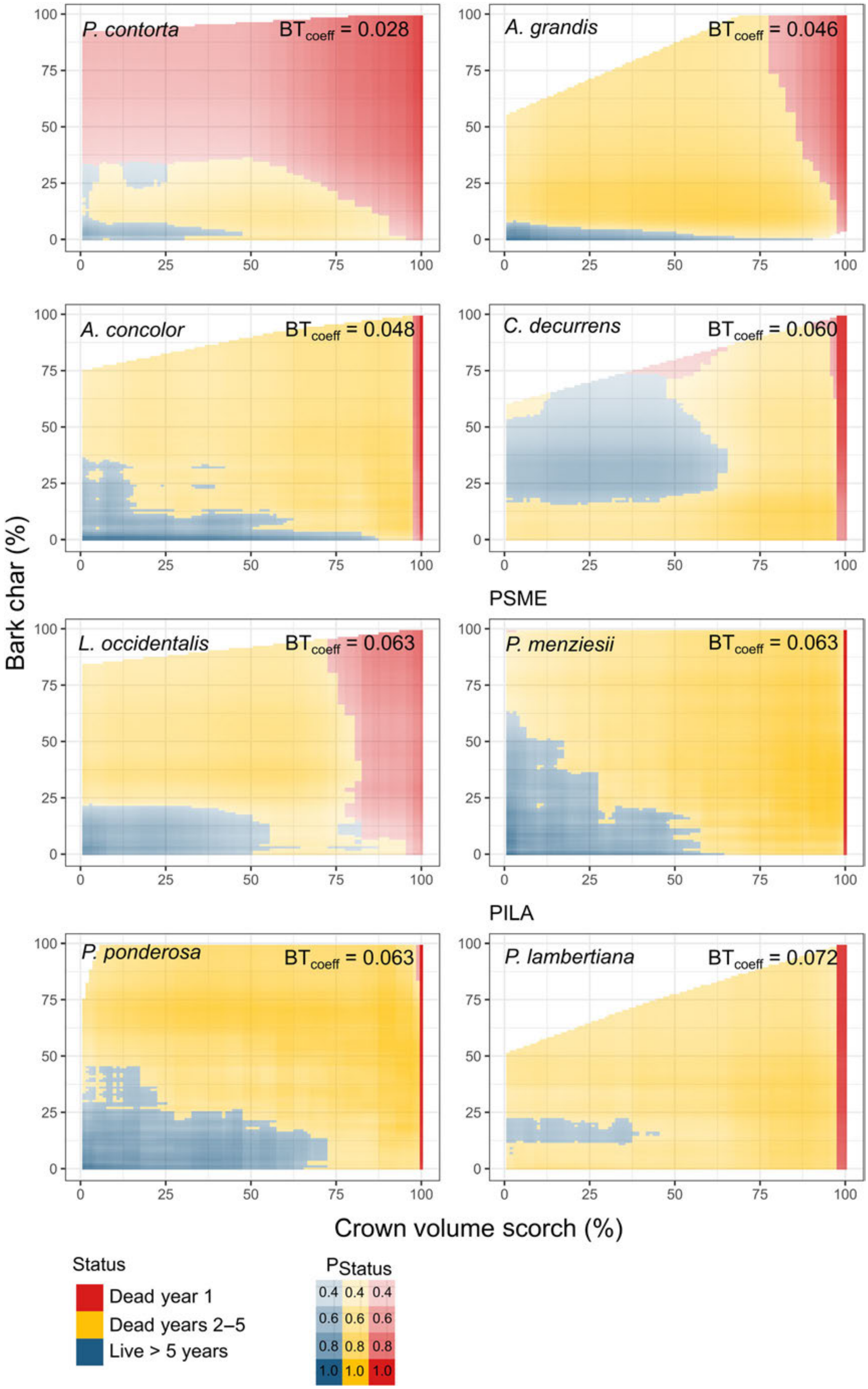

FIGURE 6 Legend on next page.

importance of bark char among species could be due to a number of factors such as bark thickness. For instance, *P. contorta* has the thinnest bark of all the species in our dataset. Thick bark insulates the cambium by reducing the conductive heat transfer from the fire through the bark to the underlying cambium (Vines, 1968). Thus, bark char on a stem with thick bark is less likely to indicate damage to the cambium than bark char on a thin-barked species (Hood et al., 2008). For example, Hood et al. (2008) found that bark char severity codes (as a categorical variable) were correlated with cambium status (live/dead). High char severity was associated with dead cambium in all species, while moderate char severity was strongly associated with dead cambium in thin-barked species (*P. contorta*, among others) but not in thick-barked species (*P. ponderosa*, *A. concolor*, *L. occidentalis*, *C. decurrens*, and *P. lambertiana*) (Hood et al., 2008).

In general, thick-barked species (e.g., *P. ponderosa*, *P. lambertiana*, *P. menziesii*, and *C. decurrens*) had higher tolerance to both crown scorch and bark char than thinner-barked species (e.g., *P. contorta*, and *A. grandis*). However, bark thickness (at least those derived from FOFEM equations) does not entirely explain the patterns observed in our data. For example, *P. lambertiana* has the highest bark thickness coefficient of the species in our dataset and is ranked as very fire resistant (Stevens et al., 2020) yet was not as tolerant to fire injury as *C. decurrens*. Similarly, *L. occidentalis*, *P. ponderosa*, and *P. menziesii* have the same bark thickness coefficients but have different patterns of predicted mortality. The relationship between *L. occidentalis* and injury variables indicated higher sensitive to fire injury although the fact that it is a deciduous species may have influenced the crown scorch measurements (i.e., scorch cannot be measured in the dormant season). Previous research suggests that *L. occidentalis* is highly fire-tolerant and has significantly lower mortality than species in mixed-conifer stands (Belote et al., 2015; Stevens et al., 2020).

We did not include bark thickness as a predictor because the bark equations from FOFEM are simply the DBH multiplied by a coefficient, so essentially they are just a rescaled DBH. Bark thickness can vary within species depending on the life stage of a tree (Jackson et al., 1999) as well as tree growth rate, with faster growing trees allocating fewer resources to bark (Shearman & Varner, 2021; Zeibig-Kichas et al., 2016). As a result, fire-induced mortality models like FOFEM and FFE-FVS can fail to accurately predict bark thickness and subsequent tree mortality. For example, Zeibig-Kichas et al. (2016) found that FFE-FVS underpredicted bark thickness for *A. concolor* and *C. decurrens* of all diameter sizes in California. For *P. concolor* and *P. lambertiana*, FFE-FVS underpredicted for smaller trees and overpredicted for larger trees in California, but overpredicted bark thickness for *P. lambertiana* and *P. menziesii* in Oregon (Zeibig-Kichas et al., 2016). Bark thickness alone may not be the best predictor of fire defense. For example, Barlow et al. (2003) found that trees that survived in burned areas had significantly rougher bark in the 0.2–0.6 cm bark thickness classes, which might suggest that bark texture on smaller trees may be a benefit to fire survival, possibly by altering the heat transfer at the fire-bark interface (Dickinson & Johnson, 2001; Shearman & Varner, 2021). The lack of complete knowledge on the importance of additional bark properties on fire survival and the fact that bark thickness is rarely linear with diameter growth indicates that further work is clearly still needed on bark thickness-diameter relationships and the factors that affect them.

Our results suggest that post-fire mortality in *P. ponderosa* and (to a lesser extent *P. lambertiana*) in later years is lower in intermediate sized trees than small and large diameter trees with moderate (50%) crown volume scorched. This result agrees with that of previous studies who found a similar U-shaped DBH-mortality distribution in *P. ponderosa* (Finney, 1999; McHugh & Kolb, 2003; Swezy & Agee, 1991) as well as in *Pinus sylvestris* (Linder et al., 1998). McHugh and Kolb (2003) suggested that larger trees, despite presumably having thicker bark than intermediate sized trees, could have higher mortality due to damage from previous fires, higher fuel loads at the base, lower carbohydrate reserves, or higher likelihood for beetle attacks. The buildup of bark slough over time at the base of old *P. ponderosa* trees can cause greater root and cambial temperatures during a fire than younger trees (Kolb et al., 2007). Old trees with lower net photosynthetic rates and higher carbon sink demands might have lower carbohydrate levels to replace and repair damaged tissues (Kolb et al., 2007; Ryan et al., 1997). Finally, thicker phloem in larger trees may be more attractive to phloem-feeding insects like bark beetles, thus increasing mortality (Kolb et al., 2007; McHugh et al., 2003; McHugh & Kolb, 2003). For example, Hood and Bentz (2007) found

FIGURE 6 Partial dependence plots showing the random forest model classification for given crown volume scorched and bark char as a percent of total height accounting for the average effect of diameter. Colors represent the class with the highest predicted probability in the random forest model with more opaque colors having higher probability. BT_{coeff} is the bark thickness coefficient used in first order fire effects model (Lutes, 2020).

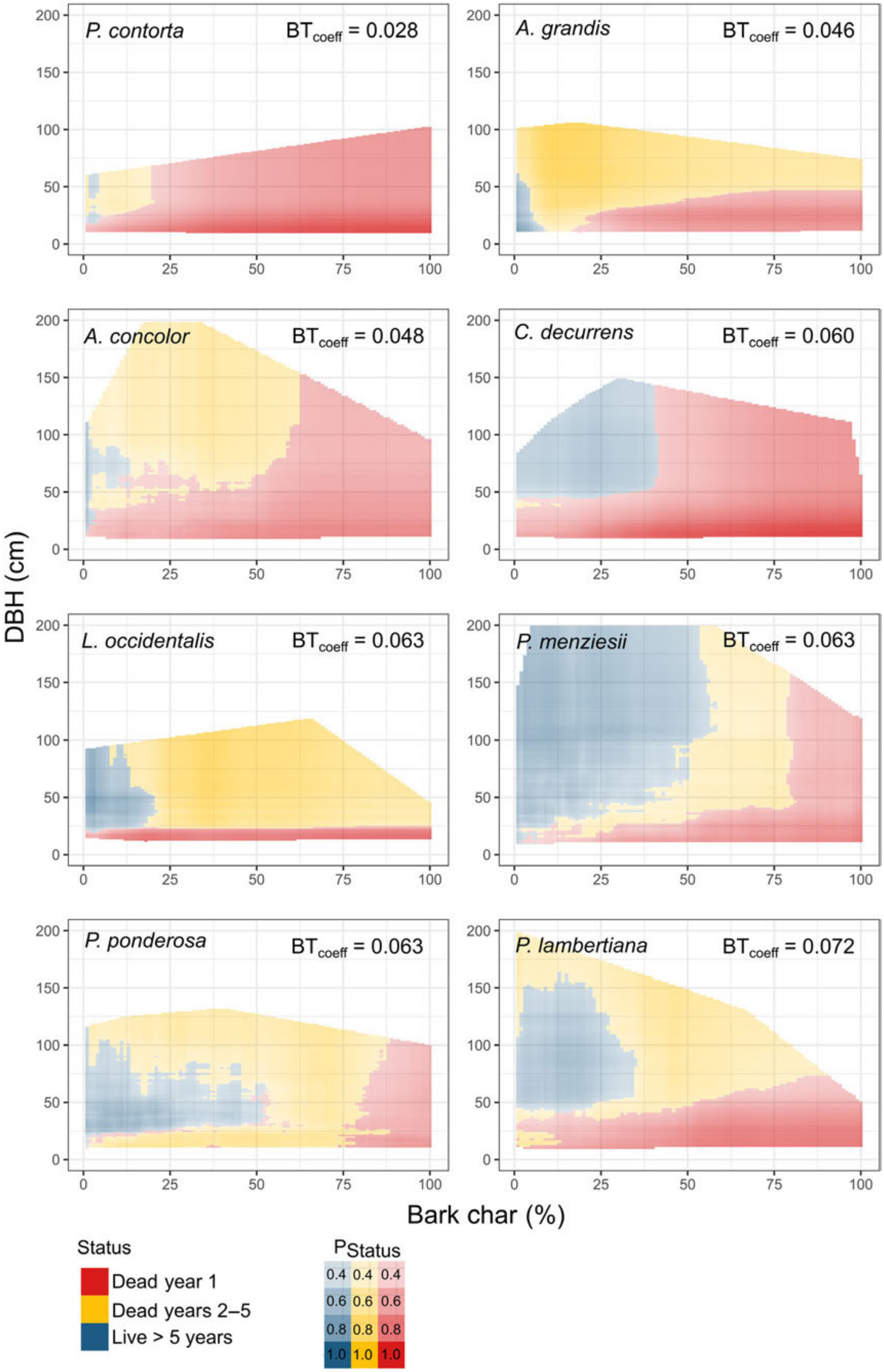

FIGURE 7 Legend on next page.

a U-shaped DBH-mortality distribution in *P. menziesii* that were burned and attacked by beetles after the fire. Increased mortality of large trees may be driven by the presence of primary bark beetles that cause mortality of a given tree species. Thus the understanding of bark beetle population dynamics is important to improve post-fire tree mortality models.

Our models predicted mortality for the more fire-sensitive species such as *P. contorta*, and *A. grandis* at low crown scorch thresholds suggesting these species are sensitive to even light amounts of scorch. This agrees with the results of Grayson et al. (2017), who reported mortality thresholds of 40% and 60% for *P. contorta* and *A. grandis* respectively. Our study however, suggests that there may be different immediate mortality and delayed mortality scorch thresholds as well as different thresholds for different sized trees. These different thresholds may explain the variability in thresholds reported in the literature. For example, previous studies in the literature on crown scorch thresholds in *P. ponderosa* has varied from 60% to 100% (Davis et al., 1968; Fowler et al., 2010; Harrington, 1993; Herman, 1954; Lynch, 1959; McHugh & Kolb, 2003; Potter & Foxx, 1984). Other explanations for this variability are uncertain, but could include season of fire. Growing season fires have been reported to have higher mortality with lower scorch than dormant season fires (Dietrich, 1979; Harrington, 1993), although McHugh and Kolb (2003) found mortality was lowest in a late June fire and Knapp et al. (2009) did not find any consistent pattern with fire season. Differences in injury terminology and measurement methods used in studies may also explain some of the differences (e.g., crown scorch, crown consumption, crown kill, Varner et al., 2021). For example, Fowler et al., 2010 found a crown volume scorch threshold of 88% for *P. ponderosa* stems that had no crown consumption, but stems with any consumption up to 40% did not have a specific threshold, rather mortality increased linearly with crown scorch. Our results indicate that future studies on scorch thresholds should take temporal mortality into account if timing of death is of interest.

Our models illustrate the utility of the random forest algorithm for post-fire tree mortality classification. Current post-fire tree mortality models such as FOFEM and other post-fire tree mortality studies that use logistic regression often find that the models have either high sensitivity and low specificity or vice versa (Cansler, Hood, van Mantgem, & Varner, 2020; Ganio & Progar, 2017; Grayson et al., 2017; Kane et al., 2017). Shearman et al. (2019) demonstrated that this pattern can be due to an unbalanced response variable in the data (e.g., more dead trees than surviving trees). For example, Cansler, Hood, van Mantgem, and Varner (2020) found that FOFEM models for thin barked species had a pattern of high sensitivity and low specificity, consistently over-predicting mortality. Thin-barked species generally have higher mortality from fire and thus the data will often be unbalanced with many dead trees and few surviving trees. In these situations, logistic regression (as well as the default random forest) models will be biased toward the majority class. Shearman et al. (2019) used balanced random forest models for predicting *Pinus palustris* mortality in southeastern USA and had more consistent sensitivity and specificity compared to logistic regression fit to the unbalanced data. Here, we show that balanced multi-class random forest models add even more insights into post-fire tree mortality models.

Our study also demonstrates the value of the FTM database. Large datasets are necessary in order to increase our understanding of the major drivers of post-fire tree mortality and the FTM database is the largest source of post-fire tree mortality data currently available (Cansler, Hood, van Mantgem, & Varner, 2020). It would be useful to standardize the predictor variables measured in future studies so that a more complete set of predictors are available as they are incorporated into the FTM database. More studies are also needed in the FTM database that survey mortality each year to improve our understanding of how different species respond to specific types of injuries over time.

CONCLUSION

Machine learning algorithms such as random forests have increasingly been applied to answer ecological questions as large, multivariate datasets have become available in the past decades (Jain et al., 2020; Liu et al., 2018). The ability of these algorithms to model interacting, nonlinear relationships and provide accurate predictions on new observations makes their potential for ecological applications very attractive (Olden et al., 2008). Jain et al. (2020) highlight the possible applications of machine learning in wildfire

FIGURE 7 Partial dependence plots showing random forest model classification for given bark char as a percent of total height and diameter at breast height (DBH) accounting for the average effect of crown volume scorched. Colors represent the class with the highest predicted probability in the random forest model with more opaque colors having higher probability. BT_{coeff} is the bark thickness coefficient used in first order fire effects model (Lutes, 2020).

science and management, including fire susceptibility, fuels characterization, burned area prediction, as well as decision making such as fuel treatments, and wildfire response. We present an improved method for predicting post-fire tree mortality that can be used by managers to help plan post-fire salvage and model future stand and landscape structure and composition. Our results suggest that fire injury predictors such as crown volume scorched and bark char perform well in predicting first year mortality, but their predictive ability declines over time for delayed mortality. Models predicting 2–5 years post-fire mortality had consistently high false negative rates, meaning that a substantial number of trees predicted to survive their fire injuries ended up dying in later years. Therefore, these models are conservative in designating which trees will die from fire and higher mortality than is predicted should be expected, especially for trees with moderate levels of injury. We identify the need for additional data that can be incorporated in the FTM database and improve prediction of delayed mortality.

AUTHOR CONTRIBUTIONS

Timothy M. Shearman conceived the idea, which was brought into focus through discussions with J. Morgan Varner, Sharon M. Hood, Phillip J. van Mantgem, C. Alina Cansler, and Micah Wright. Timothy M. Shearman analyzed the data and led the writing of the manuscript. All authors contributed critically to the early drafts of the manuscript and gave final approval for publication.

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CONFLICT OF INTEREST

All authors declare that they have no conflict of interest.

DATA AVAILABILITY STATEMENT

The FTM database (Cansler, Hood, Varner, van Mantgem, Agne, Andrus, Ayres, Ayres, Bakker, Battaglia, Bentz, et al., 2020; Cansler, Hood, Varner, van Mantgem, Agne, Andrus, Ayres, Ayres, Bakker, Battaglia, et al., 2020) is publicly available at https://doi.org/10.2737/RDS-2020-0001. R code (Shearman, 2022) is available in Zenodo at https://doi.org/10.5281/zenodo.7061866.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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