CSIRO PUBLISHING

International Journal of Wildland Fire **2012**, *21*, 1–35
http://dx.doi.org/10.1071/WF09039

Review

A review of logistic regression models used to predict post-fire tree mortality of western North American conifers

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Abstract. Logistic regression models used to predict tree mortality are critical to post-fire management, planning prescribed burns and understanding disturbance ecology. We review literature concerning post-fire mortality prediction using logistic regression models for coniferous tree species in the western USA. We include synthesis and review of: methods to develop, evaluate and interpret logistic regression models; explanatory variables in logistic regression models; factors influencing scope of inference and model limitations; model validation; and management applications. Logistic regression is currently the most widely used and available technique for predicting post-fire tree mortality. Over 100 logistic regression models have been developed to predict post-fire tree mortality for 19 coniferous species following wild and prescribed fires. The most widely used explanatory variables in post-fire tree mortality logistic regression models have been measurements of crown (e.g. crown scorch) and stem (e.g. bole char) injury. Prediction of post-fire tree mortality improves when crown and stem variables are used collectively. Logistic regression models that predict post-fire tree mortality are the basis of simple field tools and contribute to larger fire-effects models. Future post-fire tree mortality prediction models should include consistent definition of model variables, model validation and direct incorporation of physiological responses that link to process modelling efforts.

Additional keywords: fire behaviour, fire injury, modelling, prescribed fire, wildland fire.

Received 23 April 2009, accepted 8 February 2011, published online 18 November 2011

Introduction

Forest managers and ecologists have been interested in predicting post-fire tree mortality for decades. The increase in large wildfires in coniferous forests of western North America and the need to use prescribed burning to reduce fuels (Peterson and Ryan 1986; Wyant *et al.* 1986; Hood *et al.* 2007*a*) necessitate accurate post-fire predictive models of large-scale tree mortality. The ability to predict death of individual trees following fire based on physical evaluation of tree injury can also aid in post-fire salvage operations, rehabilitation and conservation efforts, and determining snag and downed wood recruitment (Mellen *et al.* 2002; Scott *et al.* 2002; Filip *et al.* 2007; Hood *et al.* 2007*a*). Stand-level prediction of post-fire mortality can prove useful for long-term planning (Peterson and Ryan 1986) and projection of future stand structures and ecological succession. Individual tree- and stand-level predictive models have been used as components in larger fire-effects models (e.g. Reinhardt *et al.* 1997; Reinhardt and Crookston 2003; Andrews *et al.* 2008), and continue to be of use in developing post-fire management scenarios (Sieg *et al.* 2006). In addition to predicting tree or stand death, models can increase our understanding of fire effects on the structure and composition of post-fire plant communities (Agee 1993), and thus ecosystem processes and function (Regelbrugge and Conard 1993).

Post-fire tree mortality models, and their associated objectives, can be put into three broader categories: (1) mechanistic, process-based models that explicitly model the underlying physical and biological processes; (2) empirically based predictive models that use fire behaviour and tree injury variables to predict individual tree mortality; and (3) larger fire-effects models that incorporate multiple post-fire processes including tree mortality to gain a comprehensive understanding of ecosystem response to fire.

Process-based mechanistic models attempt to directly model the processes involved in fire mortality and the resulting tree injury (Butler and Dickinson 2010). For example, temperature-dependent thermophysical processes are modelled to predict cambial tissue injury, and cell and bud necrosis (Dickinson and Johnson 2004; Jones *et al.* 2004; Michaletz and Johnson 2008), and a more physically complete model of heat transfer and canopy scorch has been developed by Michaletz and Johnson (2006). These models are based on an understanding of the causal mechanisms controlling the process of fire and subsequent mortality (Michaletz and Johnson 2007), and in the case of heat transfer and canopy scorch, may help predict effects of prescribed burning under certain conditions. These models may be more generalisable, but owing to their complex structure, they are difficult to use in the field to predict individual tree mortality.

Empirically based logistic regression models are typically used to predict post-fire mortality (objective 2). This technique relates the probability of tree death to explanatory variables (Hosmer and Lemeshow 2000) and was first applied to post-fire tree mortality by Bevins (1980). It has become one of the primary methods to predict individual- and stand-level mortality in the field and in larger fire-effects models. When the goal of these models is prediction and not explanation, the explanatory variables in models do not directly address the biophysical and physiological processes inherent in fire-injury-caused tree mortality.

Large-scale fire-effects models (e.g. FOFEM, FFE-FVS) incorporate many small-scale statistical and mathematical models to predict stand- or landscape-scale ecosystem response to fire. These models often incorporate logistic regression techniques to model tree mortality. Fire-effects models are useful for planning purposes and facilitating pre- and post-fire management decisions, and may provide a framework to link predictive logistic regression models to more mechanistic process-driven models (Butler and Dickinson 2010).

Our objective is to summarise, review and synthesise post-fire tree mortality logistic regression models for western coniferous species presented in peer-reviewed literature and in United States Forest Service general technical reports. We focus our review on logistic regression models for three reasons: (1) logistic regression models are the most widely reported statistical models in the literature to predict post-fire tree mortality; (2) logistic regression models are currently the only tools available to predict post-fire tree mortality, and have been shown to be practical for use in the field; and (3) logistic regression models provide a strong empirical basis for moving forward with more process-based tree mortality modelling. We summarise the explanatory variables in the models and identify where additional information is needed to improve tree mortality predictions for forest land managers. We also identify limiting features of these models and potential linkages to more physical-based process models. Our review includes a background on model development evaluation and validation, as well as a summary of the measurement of the explanatory variables, and a review of the factors that influence the potential applicability of these models for both management and research purposes.

Post-fire tree mortality logistic modelling

Model development

Post-fire tree mortality logistic regression models use post-fire observations of fire behaviour and tree injury to obtain a probability of mortality or survival of individual trees or the proportion of trees surviving over a given area and time period (e.g. 2–5 years). These models are developed to either: (1) determine the explanatory variables most associated with post-fire tree mortality; or (2) predict as accurately as possible individual or stand-level tree mortality. The first goal is focussed on the biological significance of certain variables and how they affect the response, whereas the latter is more concerned with the ability to accurately and efficiently predict the response. It is important to discern these two objectives, because as Hosmer and Lemeshow (2000) point out, it is possible to construct a model that fits the data (i.e. good estimation of the relationship between the response and explanatory variables) but is a poor predictive model.

Information criterion statistics (e.g. Akaike's Information Criterion or Bayesian Information Criterion; AIC and BIC respectively) rank the evidence in the data to select good models from a set of *a-priori* chosen models (Burnham and Anderson 2002). Information criteria are generally preferred over multiple hypothesis tests because model-building is not inherently a hypothesis-testing problem and because model selection via hypothesis testing has been shown to include unimportant variables (Flack and Chang 1987; Burnham and Anderson 2002). Moreover, information criteria explicitly value the parsimony of the model by including a penalty for an increased number of variables. These methods have been rarely used in post-fire tree mortality studies (AIC; van Mantgem and Schwartz 2003; Sieg *et al.* 2006), but may be the most appropriate given the *a-priori* knowledge of variables used to classify post-fire tree mortality.

Until recently, the majority of research has used a statistical hypothesis-testing framework to identify variables indicative of post-fire tree mortality processes and how these variables may interact (Ryan *et al.* 1988). However, a large body of knowledge has been developed regarding the relationships and importance of certain variables in explaining post-fire tree mortality, particularly in the case of Douglas-fir and ponderosa pine (Fowler and Sieg 2004). Developing *a-priori* models based on this body of knowledge would further our understanding of post-fire tree mortality and its prediction.

Model evaluation

When the goal of modelling is accurate prediction of mortality at an individual tree or stand level, the accuracy of model classification is essential. It is conceivable that a logistic regression model fits a set of data well, but classification (i.e. prediction of trees as dead or alive) accuracy is poor (Hosmer and Lemeshow 2000). Model accuracy is evaluated by comparing the observations with the predicted values. As a model predicts the probability of mortality and not whether a tree lives or dies, a probability is selected as the cut-off between mortality and survival (i.e. decision criteria). For example, if the decision criterion is set at 0.6, then any individual tree with a probability of mortality greater than or equal to 0.6 is classified as dead, whereas any value less than 0.6 results in a tree being classified as surviving (e.g. Raymond and Peterson 2005; Thies *et al.* 2006). Classification of model predictions as correct or incorrect for one to several decision criteria levels has been used to describe model accuracy (e.g. Hood and Bentz 2007). It is important to understand how model accuracy might change as the decision criteria become more or less conservative depending on the objectives of the application.

Saveland and Neuenschwander (1990) proposed evaluating model accuracy using Receiver Operating Characteristics (ROC) methodology. This approach allows one to evaluate sensitivity and accuracy of models over a range of decision criteria as measured by the area under an ROC curve (AUC) (the plot of correct predictions against false positives). This tool provides information across the entire range of decision criteria, and has been widely applied in evaluating models (Regelbrugge and Conard 1993; Finney 1999; McHugh and Kolb 2003; van Mantgem and Schwartz 2004; Keyser *et al.* 2006; Kobziar *et al.* 2006; Breece *et al.* 2008; see Table A3 for use of ROC). However, when standard errors or confidence intervals for the AUC statistic are not reported, the degree to which the estimated AUC will vary from sample to sample is not known. It may be that, while the point estimate of the AUC is sufficiently close to one, the confidence interval would indicate a wide range of potential values for the true AUC. Unless measures of precision such as standard errors or confidence intervals are provided, the interpretation of ROC curves and associated AUCs is problematic.

It is also significant to note that the accuracy of most models is assessed using the same dataset from which the model was derived. Thus, it is not surprising that classification accuracy is reported to be high when evaluating a model owing to the use of the same data from which it was developed. A model showing good fit to data may also accurately predict the outcome(s) within that same dataset. As we discuss further in the section on model validation, a more accurate test of the predictive ability of a model would be to test it on an independent set of data (e.g. Keyser *et al.* 2006; Sieg *et al.* 2006; Hood *et al.* 2007*a*).

Model validation

Model validation is a statistical technique used to test the accuracy of independent applications of models. Since 1980, only 13 of the >100 reported models have been validated using independent data not used in model development (Tables A1–A4). Although an increased effort is apparent, additional work may be necessary to validate previous models using data sources external to those used to develop models.

Validation techniques vary from simple cross-validation methods, which use subsets of the data used to build the model to test the model (Wyant *et al.* 1986; Regelbrugge and Conard 1993; Keyser *et al.* 2006), to the use of entirely independent sets of data to evaluate one to several models (Weatherby *et al.* 1994; Sieg *et al.* 2006; Hood *et al.* 2007*a*, 2010; Breece *et al.* 2008). Several factors should be considered when validating previously developed models. First, should models based on a dataset with limited scope and small sample size be considered for validation? Models resulting from limited sampling may not have wider application. Second, what is the scope of inference for the original dataset and the validation dataset? The scope of inference for the original dataset determined by the sampling method provides the geographical and temporal extents and resolution to which the model can be applied. If an extension of the scope can be justified scientifically (by means beyond statistical sampling), then validation using a dataset from a broader scope may be possible.

Validation of previously published models (Ryan and Reinhardt 1988; Ryan and Amman 1994), using data from a wide geographic scope, indicate large fluctuations in accuracy within fires (based on ROC values), between fires and between species (Hood *et al.* 2007*a*). Models were examined at both the scale of individual fires and within a species across fires in similar and different regions. Some of this variation is likely due to the differences between trees (e.g. species and diameter ranges) from which the model was developed and trees to which the model was applied. More recently, Hood *et al.* (2010) validated several previously published models (Mutch and Parsons 1998; Stephens and Finney 2002). These comparisons also resulted in variation in model prediction accuracy across species for the different models.

Further validation efforts could facilitate a dialogue focussed on whether model building should continue (at least for some tree species and geographic areas), or if model refinement and application should be the next step. Moreover, large-scale validation could assess the limitations and applicability of models in different biophysical settings than those in which they were developed. We recommend validation efforts focus on those models that have large sample sizes and spatial scope (e.g. Ryan and Reinhardt 1988; Sieg *et al.* 2006; Hood *et al.* 2010) and were developed using more rigorous modelling methodologies (e.g. Sieg *et al.* 2006). Research to date also indicates models should be developed from at least 3 years of post-fire data to capture delayed mortality, and therefore models with shorter post-fire records should not be considered. Finally, to allow for comparison with the original evaluation of models, we suggest ROC methods be implemented in future validation endeavours.

Model scope and limitations

The model's scope of inference is central to its proper application and in understanding its limitations. For example, many studies have adequately described fire characteristics, but often lacked critical information such as the range of tree diameters (e.g. Wyant *et al.* 1986; Borchert *et al.* 2002) and the number and size of plots sampled (e.g. Bevins 1980; Peterson and Arbaugh 1986; Peterson and Arbaugh 1989), as well as the current environmental conditions under which the data was collected. For instance, the ranges of diameter at breast height (DBH) were reported for only 19 of the 33 total studies of ponderosa pine and Douglas-fir. This lack of information can hinder extension of future research (e.g. larger meta-analysis or validation) or model application.

Attributes contributing to the scope of inference are: the number of years post fire the model prediction is based on, the number and types of fires (e.g. wildfire *v.* prescribed fire; spring *v.* summer or autumn burns), the number of sites sampled, the number and size of plots sampled, the study area represented by those sample units, the total number and diameter range of trees sampled (Tables A1, A2), and whether different tree species were modelled separately or not (Tables A3, A4). For example, Hood *et al.* (2007*a*) found that a model they validated performed poorly for several species for which it had not been developed, and for larger-diameter yellow pines (ponderosa and Jeffrey pine) that were outside the diameter range of the original dataset. Similarly, Weatherby *et al.* (1994) found that the same model underpredicted secondary mortality in large Douglas-fir owing to Douglas-fir beetle (*Dendroctonus pseudotsugae*), which was unaccounted for in the model.

The scope, limitations and applicability of logistic regression models also depend on the distribution of explanatory variables used to build the model. In an experimental setting, one would create combinations of explanatory variables across the full range of all explanatory variables. Post-fire studies are observational studies, so a pragmatic way to adequately capture the range and combinations of explanatory variables is to rely on large samples of observations that are well distributed over the range of variation of the explanatory variables. Sample sizes (per species) in the reviewed studies range from 51 to 5083 trees. Only eight of the studies used a sample size greater than 1000 trees to develop post-fire tree mortality logistic models. Furthermore, standard errors of estimated model coefficients and covariances among the coefficients are rarely reported in the literature (e.g. McHugh and Kolb 2003; McHugh *et al.* 2003; Kobziar *et al.* 2006). The uncertainty of future predictions from a model is estimated from these statistics. If they are not reported along with the model estimates, then it is not possible to determine the precision of future predictions.

The scope at which a particular model should be applied also has temporal and spatial attributes. Models constructed using 1-year post-fire data (e.g. Bevins 1980; Peterson and Arbaugh 1989; Finney and Martin 1993) may not necessarily apply 3 years post fire. It has generally been observed that post-fire tree mortality returns to background mortality rates within 3–4 years after fire. Harrington (1993) reported for a prescribed burn in ponderosa pine that 80% of mortality observed over a 10-year period occurred by year 3 and 90% by year 4. Similarly, Keyser *et al.* (2006) found that mortality post fire declined sharply by year 3 following a wildfire in ponderosa pine. However, less than 10 studies (prescribed and wildfire) measured mortality for longer than a 3–5-year period, and only four prescribed fire studies have tested this hypothesis using control plots for comparisons (Harrington 1993; Mutch and Parsons 1998; van Mantgem *et al.* 2003; Thies *et al.* 2006). Swezy and Agee (1991) indicate that they measured mortality on both burned and unburned plots, but never discuss the trend of mortality over time between the two. However, Mutch and Parsons (1998) examined pre- and post-fire mortality annually and found that after 5 years, mortality had not returned to pre-fire rates. Past (e.g. Saveland and Neuenschwander 1990; Kobziar *et al.* 2006; Raymond and Peterson 2005) and future studies are of little use in understanding delayed post-fire tree mortality if less than 3 years of data are collected to develop or validate them.

It is also likely that the length of time mortality occurs as a direct result of fire is site-specific, and may limit the applicability of many models. Environmental stressors such as prolonged drought and insect outbreaks following fire, as well as physiological responses of some tree species, may affect the duration of post-fire tree mortality. Clearly, more work is needed to elucidate the temporal dynamics of post-fire tree mortality in both prescribed and wildfires, and across different forest types.

Spatial scope of inference should also be considered when evaluating model strength and applicability. For example, the number of sample plots within and across fires, and the number of fires sampled and their physical locations are important considerations when interpreting the spatial extent of model applicability. Recently, studies have begun to address the subject of region-to-region model applicability. Sieg *et al.* (2006) developed a multisite model for ponderosa pine from wildfires in Arizona, Colorado, South Dakota and Montana. This model performed extremely well in validation efforts on a separate fire in the Black Hills, SD. Although a portion of the data used to develop the model was from the Black Hills National Forest, the results indicate that applicability beyond the original spatial scope is possible with robust sampling and model-building methods. At a smaller spatial scale, the level at which data are collected is important as well. Models built with tree-level data may have the same model structure as models built from stand-level data (i.e. plot averages of explanatory variables). Although a model can be used to predict individual tree mortality or the proportion of mortality for a stand, the scale of the data that is input into the model needs to be considered.

Methods

We reviewed several scientific literature databases, reviewed citations in scientific papers of post-fire tree mortality, and used knowledge of existing literature from several researchers of post-fire tree mortality. Each citation was carefully reviewed and information relevant to the objectives of the synthesis was summarised. This information was then collated into tables describing characteristics of each study (e.g. geographic location, fire type), the scope of inference of the study (e.g. study area, sample size, species) and model summary statistics (i.e. the model and its coefficients, evaluation and validation statistics). We used this tabular information to identify and synthesise important features of the models and the studies from which they were developed, as well as to identify strengths and weaknesses of specific studies. The tables are used throughout the paper as a basis from which we discuss fire behaviour and injury variables, model interpretation, evaluation, validation and factors influencing the scope of inference and applicable use of models in management scenarios. We have provided these tables (Tables 1, 2, A1–A4) as a reference appropriate for current research and management as well as future efforts in model development and validation.

Results and discussion

Tree species and geographic regions

The 33 studies we found published in peer-reviewed journals or USDA Forest Service general technical reports focussed on 19 coniferous tree species and three hardwood species (*Quercus kelloggii*, *Q. chrysolepis* and *Lithocarpus densiflorus*), occurring in a variety of forest types (Tables 1, 2) across the western United States (Fig. 1). The bulk of this work has emphasised ponderosa pine and Douglas-fir (21 and 11 studies respectively; Fig. 2). In addition, incense-cedar (*Calocedrus decurrens*), true firs (*Abies concolor*, *A. lasicarpa* and *A. magnifica*), lodgepole pine (*Pinus contorta*) and sugar pine (*Pinus lambertiana*) make up the majority of research to date, with all other tree species (Table A5) have only been examined once.

Geographically, the Northern Rocky Mountains (Bevins 1980; Peterson and Arbaugh 1986; Ryan and Reinhardt 1988; Ryan *et al.* 1988; Ryan 1990; Saveland and Neuenschwander 1990; Hood and Bentz 2007; Hood *et al.* 2007*b*, 2007*c*) and the Sierra Nevada of northern and central California (Regelbrugge and Conard 1993; Mutch and Parsons 1998; Stephens and Finney 2002; van Mantgem *et al.* 2003; van Mantgem and Schwartz 2004; Schwilk *et al.* 2006; Kobziar *et al.* 2006) are the

Table 1. Site, fire and tree species characteristics of post-fire prescribed burning studies applying models to predict tree mortality
Study code relates to Fig. 1 and Appendices 1–5. DBH, diameter at breast height; NR, not reported in publication

Study code Author(s) (year)	Region (geographic range)	Elevation (m)	Forest type	Tree species modelled	DBH range (cm)	Season
1A Bevins (1980)	Northern Rockies (MT)	NR	Western larch Douglas-fir	Douglas-fir	12.7–48.0	NR
1B Ryan and Reinhardt (1988)	Western Cascades (OR, WA) Northern Rockies (ID, MT)	NR	Douglas-fir Western hemlock Mixed conifer	Douglas-fir Western red cedar Western hemlock Western larch Engelmann spruce Lodgepole pine Subalpine fire	8–166 13–89 13–69 13–90 13–95 13–53 10–41	Spring Summer Autumn
1C Wyant *et al.* (1986)	East slope Colorado Front Range	2550–2700	Upper montane–mixed conifer	Douglas-fir Ponderosa pine	NR	Autumn
1D Ryan *et al.* (1988)	Northern Rockies (western MT)	1460	Western larch–Douglas-fir	Douglas-fir	NR	May–June September–October
1E Harrington and Hawksworth (1990)	North-western Arizona	NR	Ponderosa pine	Ponderosa pine	NR	August
1F Saveland and Neuenschwander (1990)	Northern Rockies (northern ID)	NR	NR	Ponderosa pine	5–70	Autumn
1G Finney and Martin (1993)	NW coastal CA	240–450	Redwood Douglas-fir	Coast redwood	NR	Early and late season
1H Harrington (1993)	South-western CO	2300	Ponderosa pine	Ponderosa pine	3.8–33.8	Late spring, summer, autumn
1I Mutch and Parsons (1998)	Southern Sierra Nevada (CA)	2092–2207	Mixed conifer	White fir Sugar pine	1.0–180.0	Late season
1J Stephens and Finney (2002)	Southern Sierra Nevada (CA)	2010–2070	Mixed conifer	White fir Sugar pine Ponderosa pine Incense-cedar California black oak Giant sequoia	5–55 5–60 5–60 5–60 5–40 15–100	Late season
1K, 1L McHugh and Kolb (2003) McHugh *et al.* (2003)	Northern AZ	2225–2255	Ponderosa pine	Ponderosa pine	7.4–44.5	September
1M van Mantgem *et al.* (2003)	Southern Sierra Nevada (CA)	2033–2202	Mixed conifer	White fir	0–160	October

(*Continued*)

Table 1. (Continued)

Study code Author(s) (year)	Region (geographic range)	Elevation (m)	Forest type	Tree species modelled	DBH range (cm)	Season
1N						
van Mantgem and Schwartz (2004)	Central Sierra Nevada (CA)	Low elevation	Mixed conifer	Ponderosa pine	0–15	Summer
1O						
Thies *et al.* (2005, 2006)	Southern Blue Mountains (OR)	1570–1740	Ponderosa pine–western juniper	Ponderosa pine	NR	Autumn Spring
1P						
Schwilk *et al.* (2006)	Southern Sierra Nevada (CA)	1900–2150	Old-growth mixed conifer	White fir Red fir Sugar pine Jeffrey pine Ponderosa pine	>10	June September October
1Q						
Kobziar *et al.* (2006)	North central Sierra Nevada (CA)	1100–1400	Second-growth mixed conifer	Incense-cedar White fir Tanoak Ponderosa pine Douglas-fir	2.5–76 2.5–76 2.5–25 2.5–25 2.5–51	November
1R						
Breece *et al.* (2008)	AZ, NM	2100–2500	Ponderosa pine	Ponderosa pine	13.0–50.0	September–December
1S						
Hood *et al.* (2007*a*)[A]	AZ, CA, ID, MT, WY	NR	Varying	Lodgepole pine Whitebark pine Engelmann spruce Red fir Western hemlock Subalpine fir White fir Incense–cedar Ponderosa pine[B] Jeffrey pine[B] Douglas-fir Western larch Sugar pine	10.2–56.4 12.4–58.9 10.4–85.1 15.2–104.6 13.0–44.2 10.2–75.2 25.4–15.7 25.4–166.4 6.3–178.1 6.3–178.1 10.2–105.4 10.2–98.8 26.2–106.4	NR
1T						
Conklin and Geils (2008)	NM	2195–2560	Second-growth ponderosa pine	Ponderosa pine	NR	March September October November

[A]Study validating Ryan and Amman (1994) using both prescribed and wildfire data.
[B]Ponderosa pine and Jeffrey pine combined and modelled as yellow pine group.

Table 2. Site, fire and tree species characteristics of post-fire wildfire studies applying models to predict tree mortality
Study code relates to Fig. 1 and Appendices 1–5. DBH, diameter at breast height; NR, not reported in publication

Study code Author(s) (year)	Region (geographic range)	Elevation (m)	Forest type	Tree species modelled	DBH range (cm)	Season
2A						
Peterson and Arbaugh (1986)	Northern Rocky Mountains (MT, ID, WY)	NR	NR	Douglas-fir Lodgepole pine	≥13	Summer
2B						
Peterson and Arbaugh (1989)	Western Cascades (OR, WA)	NR	NR	Douglas-fir	≥13	Spring
2C						
Regelbrugge and Conard (1993)	West slope Sierra Nevada (Central CA)	800–1300	Mixed conifer	Ponderosa pine Incense-cedar California black oak Canyon live oak	9–114 11–76 9–51 10–71	Late season
2D						
Borchert *et al.* (2002)	Central coast (CA)	730–1160	Pine and pine–oak	Gray pine Coulter pine	NR	Late summer
2E, 2F						
McHugh and Kolb (2003) McHugh *et al.* (2003)	Northern AZ	2072–2195 2134–2255	Ponderosa pine	Ponderosa pine	10.2–91.4 22.9–106.2	Spring Summer
2G						
Raymond and Peterson (2005)	South-western OR	670–1030	Douglas-fir–knobcone pine Sugar pine	Douglas-fir	NR	July–November
2H						
Sieg *et al.* (2006)	Northern AZ North-central CO Western SD South-eastern MT	2256–3048 1829–2560 1525–2134 981–1274	Ponderosa pine	Ponderosa pine	5.1–106.9	May–July June August July
2I						
Keyser *et al.* (2006)	South-western SD	1500–2100	Ponderosa pine	Ponderosa pine	<25	August
2J						
Hood *et al.* (2007*d*)	Southern Cascades–southern Sierra Nevada (CA)	1400–2750	Mixed conifer Interior ponderosa pine	White fir Incense-cedar Jeffrey and ponderosa pine Red fir	15.2–152.7 25.4–166.4 25.4–160.8 15–105	July August September
2K						
Hood and Bentz (2007)	South-western MT North-western MT Western WY	1989–2006 1402–1780 2073–2207	Douglas-fir Lodgepole pine Mixed conifer	Douglas-fir	12.7–105.4	July August July
2L						
Hanson and North (2009)	Central Sierra Nevada (CA)	NR	Mixed conifer	Ponderosa pine Jeffrey pine Red fir	25–>75	September August
2M						
Hood *et al.* (2010)	North, central, south-central CA		Mixed conifer Ponderosa pine	Incense-cedar White fir Sugar pine Jeffrey and ponderosa pine	25.4—166.4 25.4–152.7 25.7–188.0 25.4–160.8	July August September

most frequently studied regions. Other regions studied include Oregon and Washington (Ryan and Reinhardt 1988; Peterson and Arbaugh 1989; Raymond and Peterson 2005; Thies *et al.* 2006), coastal California (Finney and Martin 1993; Borchert *et al.* 2002), northern Arizona and New Mexico (McHugh and Kolb 2003; McHugh *et al.* 2003; Sieg *et al.* 2006; Hood *et al.* 2007*a*; Breece *et al.* 2008), and western South Dakota (Keyser *et al.* 2006; Sieg *et al.* 2006).

It is unclear whether more data and models are needed for unstudied species and geographic regions before further validation of current models is undertaken. Research may be needed to determine the differences in physiological responses to fire-related injury and damage among species but also among trees from one species in different environments.

Variables used to predict post-fire tree mortality

Observations of post-fire injury and tree mortality from early in the 20th century (Miller and Patterson 1927; Salman 1934; Connaughton 1936; Herman 1950, 1954) offered guidelines for determining mortality based on thresholds of crown scorch, charred bark and cambium mortality. The first published predictive model (Bevins 1980) used crown injury variables viewed as important in several earlier studies (e.g. Lynch 1959; Wagener 1961; Dietrich 1979). Since then, numerous studies using a similar array of explanatory variables have examined immediate and delayed post-fire tree mortality for 19 different conifer species. The 116 models reviewed in the present paper include 60 different tree, insect and fire behaviour and injury variables (see Tables 1, 2, A3).

A lack of clear and consistent definitions of measurements and variables is evident within and between the fire behaviour and tissue injury categories (see Table A3). In addition, there appears to be little consensus regarding predictors of mortality, yet many of these post-fire tree mortality explanatory variables reflect the same underlying physiological disruption by injury following fire. These explanatory variables are generally

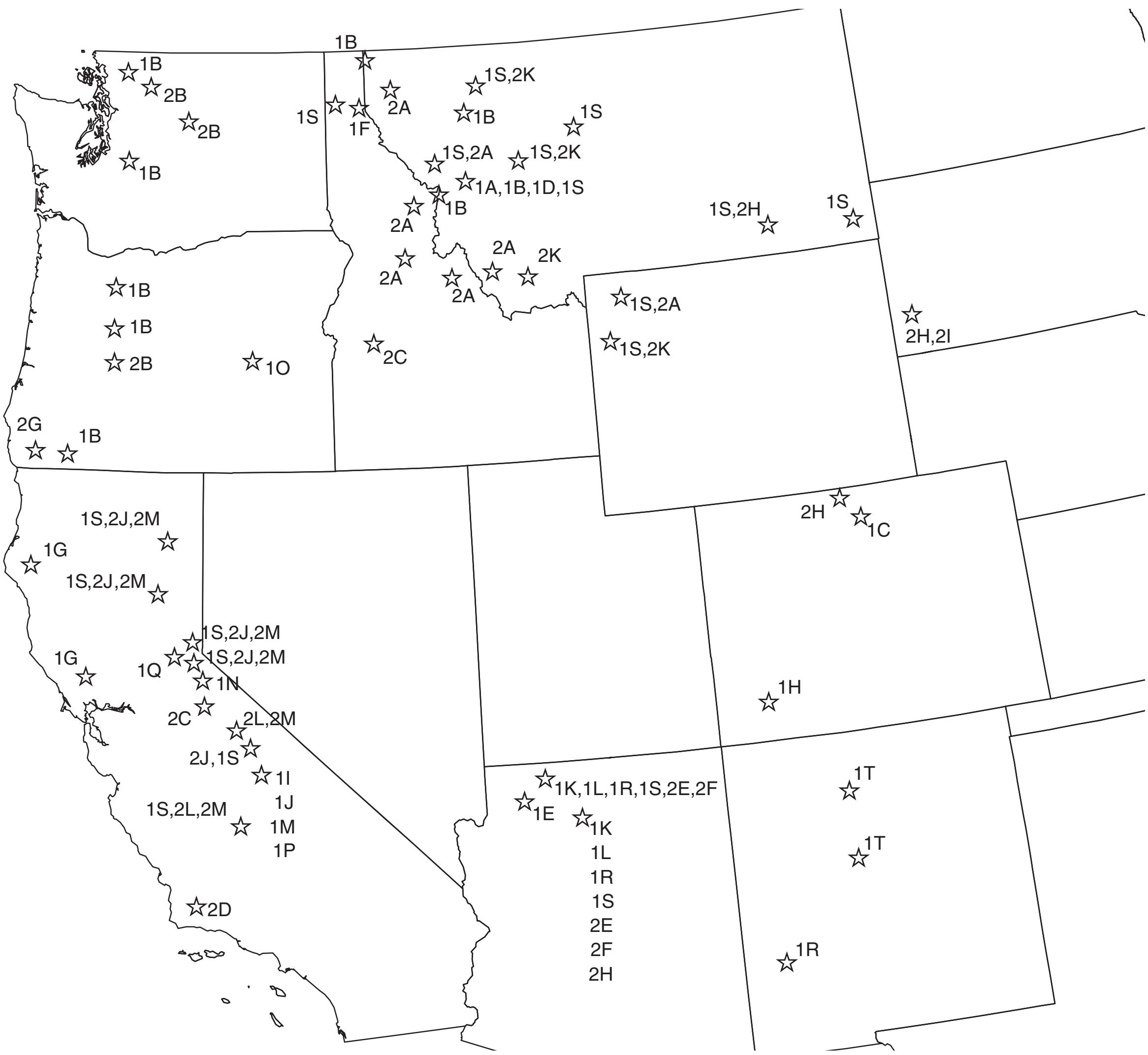

Fig. 1. Locations of post-fire tree mortality studies of coniferous tree species in the western North America. Number (1, prescribed, and 2, wildland fire) and letter indicate study code in Tables and Appendices 1–5.

consistent among species (Fig. 3), regions and forest types, but differ in how they were measured or applied in the model.

Fowler and Sieg (2004) recently reviewed the methods and measurements used to predict post-fire tree mortality for Douglas-fir and ponderosa pine. Although limited to two species, many of the explanatory variables they discussed are commonly used for other conifer species (e.g. Ryan and Reinhardt 1988; Stephens and Finney 2002; Hood *et al.* 2007*d*) as well as hardwoods (e.g. Harmon 1984; Brown and DeByle 1987; Regelbrugge and Conard 1993). They pointed out that the variables used to predict post-fire mortality fall into two general categories: those focussed on indicators of fire behaviour (e.g. crown and stem scorch height), and those indicative of tissue injury to different portions of the tree (e.g. crown volume scorched and bole char). The use of mortality explanatory variables such as the volume of crown consumed or killed and measures of cambium mortality linked injury caused to trees during fire and subsequent effects on tree vigour and physiological capacity. Alternatively, measures such as bole and crown scorch height quantify fire behaviour by providing an estimate of flame length during a fire, and indirectly providing information on possible injury to cambial tissue or foliage.

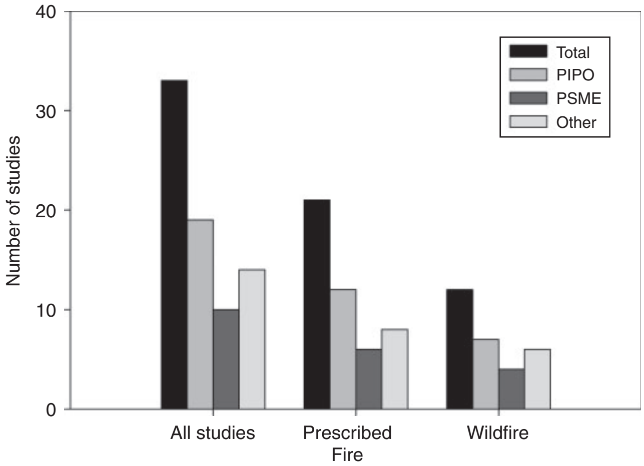

Fig. 2. Total number of post-fire tree mortality modelling studies and the number of those that examined prescribed fire and wildfire for Douglas-fir (PSME), ponderosa pine (PIPO) and other conifer species in western North America.

Throughout the literature, variables indicative of fire effects to the crown and stem continue to be the most widely used explanatory variables of post-fire tree mortality (Fig. 3). Often a combination of crown and stem variables, or an injury-resistance variable such as diameter or bark thickness, has been shown to accurately predict post-fire tree mortality. In addition to crown and stem injury variables, explanatory variables related to ground fire severity (i.e. fuel consumption on the forest floor) and fireline intensity (i.e. $\mathrm{kW\,m^{-1}}$), variables of post-fire mortality include insect attack measures and predictors of tree vigour and predisposition to mortality. More in-depth discussion of these six categories follows.

Crown injury

Crown injury variables have been the most widely used (Fig. 3) and discussed post-fire tree mortality explanatory variables in the literature. Injury to foliage and buds in the crown links fire behaviour to physiological effects and subsequent tree mortality via the loss of photosynthetic material. Only one study in the current review (Regelbrugge and Conard 1993) did not estimate crown predictors for use in models. All other studies, for both prescribed and wildfire, estimated and reported at least one crown variable as significant in a logistic model regardless of the tree species modelled. Ryan and Reinhardt (1988) and Sieg *et al.* (2006) both asserted that variation in

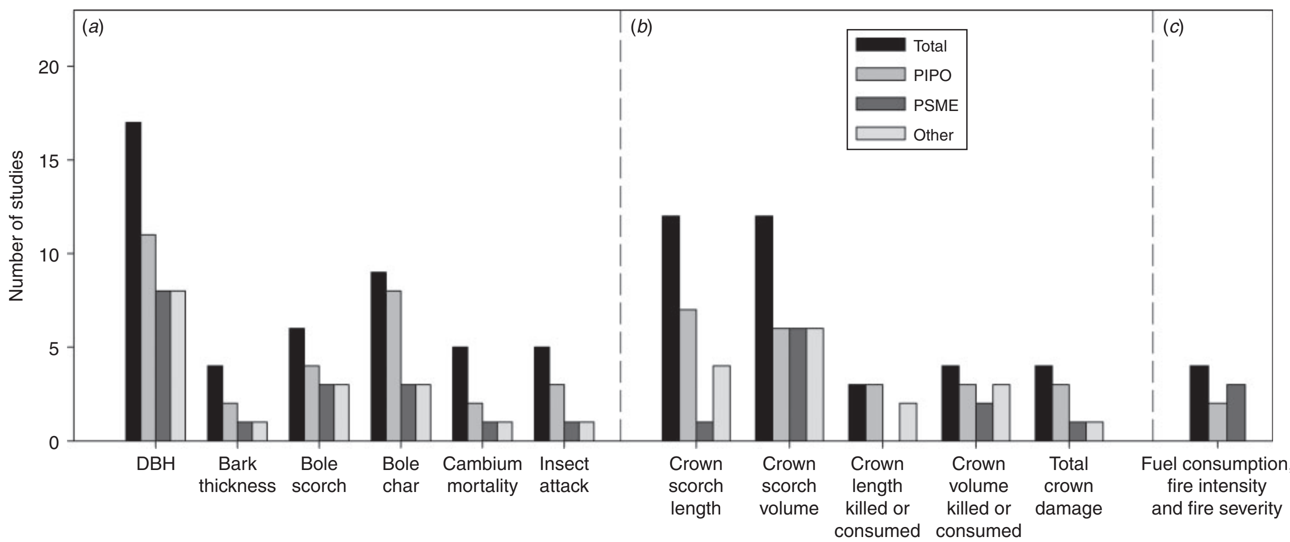

Fig. 3. The number of post-fire tree mortality modelling studies that have found the different tree bole (*a*), tree crown (*b*), and fuel consumption, fire intensity and fire severity (*c*) significant for Douglas-fir (PSME), ponderosa pine (PIPO) and other conifer species in western North America. DBH, diameter at breast height.

crown injury is not strongly associated with species, as compared with other tree-level variables such as bark thickness. However, questions still exist concerning crown injury to less frequently studied fire-resistant species such as western larch (*Larix occidentalis*).

Injury to tree crowns during fire by means of scorch, consumption and bud kill has been estimated in various ways. Percentage crown volume scorched, percentage crown length scorched, percentage crown volume killed (i.e. crown consumption or bud kill), percentage crown length killed and total crown injury (percentage crown volume scorched + percentage crown volume killed) are the most common estimates of crown injury. Peterson and Ryan (1986) point out that empirical evidence suggests that post-fire mortality is much more dependent on bud kill than foliage scorch. However, not until Finney (1999), and more recently Thies *et al.* (2006), were needle scorch and bud kill explicitly measured separately. Finney (1999), an internal report, lacks specific information and peer review necessary to judge the strength of this work. Thies *et al.* (2006) estimated needle scorch as a proportion of crown length rather than the more commonly used estimates of crown volume scorched or killed. They also incorporated refoliation (referred to as 'regreen') of the crown in the growing season following fire. Recently, Hanson and North (2009) developed models specifically for trees with significant portions of scorched crown that produce new foliage, or 'flush', following fire. Their results indicate that if flushing is not taken into account, overestimates of mortality will occur.

The single most commonly applied, and reportedly the most accurate (Peterson 1985) measure of crown injury is crown volume scorched. Peterson and Arbaugh (1986) found that the volume of crown scorched was highly correlated with scorch height, and Hood *et al.* (2010) found that both crown length scorched and crown volume scorched contributed to predictive accuracy. Measures such as crown scorch height reflect fire behaviour and infer possible effects to tree crowns, whereas scorch volume or volume killed measures the reduction in photosynthetic capacity directly. Sieg *et al.* (2006) found that the best post-fire predictor for ponderosa pine tree mortality across several fires in different regions was crown injury alone (crown volume scorched and crown volume consumed). Their findings suggest that these two variables used separately within a model, rather than combined into the single variable of total crown damage (McHugh and Kolb 2003), were more significant. They attributed this to differences in the physiological ramifications of crown scorch and crown consumption, as well as to tradeoffs between photosynthetic capacity and reduced transpirational demands with the loss of lower crown foliage. More recent findings by Hood *et al.* (2010) also substantiate crown injury measurements as strong post-fire tree mortality predictors.

Thresholds of crown injury and post-fire tree mortality have been discussed less frequently. Foliage loss in the lower parts of tree crowns may have significantly different effects on photosynthesis than consumption and scorch in the upper crown. The first documentation of thresholds came from early studies by Herman (1954) and Lynch (1959). Since then, several studies have found thresholds in which mortality rates dramatically increase when a certain percentage of crown scorching is exceeded (e.g. Borchert *et al.* 2002; McHugh and Kolb 2003), whereas many others have reported a smooth relationship between mortality and crown injury. The identification of injury thresholds has resulted in the inclusion of crown scorch classes in some logistic prediction models (e.g. Harrington 1993; van Mantgem and Schwartz 2004). The use of crown vigour classes (e.g. Swezy and Agee 1991; Kolb *et al.* 2007) may be an additional variable that has not been widely tested and could improve post-fire mortality predictions.

Measurements of fire effects to tree crowns are the single most effective predictors of post-fire tree mortality regardless of species, region or fire type, or whether they reflect fire behaviour or explicit injury to the crown. There are many different estimation methods and definitions (or lack thereof) of crown injury variables. This will limit future model comparisons or validation efforts because the data are not similar.

Current process modelling research continues to investigate crown injury (Linn and Cunningham 2005; Michaletz and Johnson 2006; Mell *et al.* 2007) and associated physiological responses (Kavanagh *et al.* 2010). These works provide a greater mechanistic understanding and linkage between fire behaviour, crown injury and tree mortality.

Stem injury and resistance to injury

Crown injury is reported to be the single best predictor of post-fire tree mortality in logistic regression models, yet the inclusion of fire behaviour (e.g. stem scorch height), stem injury (e.g. bole char and cambium mortality) or heat resistance (e.g. bark thickness, diameter) variables have been shown to significantly improve estimates of post-fire tree mortality (e.g. Peterson and Arbaugh 1986, 1989; Ryan and Reinhardt 1988; McHugh and Kolb 2003; Keyser *et al.* 2006; Kobziar *et al.* 2006; Thies *et al.* 2006; Hood *et al.* 2010). Reduction in cambial function via tissue necrosis (i.e. girdling) has been shown to significantly increase the probability of mortality, alone or in combination with other injuries (Dickinson and Johnson 2001). Results from a biophysical process-based model by Michaletz and Johnson (2008) suggest that cambial necrosis may be more important than bud necrosis in tree crowns for the two species of conifers they studied (*Picea glauca* and *Pinus contorta*). However, given their model was only able to predict tree mortality once 100% girdling of the stem was reached, the generalisation of these results is uncertain.

Very few logistic regression models make use of stem injury predictor variables exclusively (e.g. Ryan *et al.* 1988). Measurements indicative of resistance to fire injury (i.e. tree diameter and bark thickness; Fig. 3) are the most common measurements of tree stems that contribute to predictive power in post-fire tree mortality studies. Fire resistance variables such as tree diameter and bark thickness have been widely used predictor variables because they indicate a tree's resistance to stem injury from heat and are easy attributes to measure or calculate. Temperatures lethal to cambium tissue have been shown to increase with the square of bark thickness (Fahnestock and Hare 1964; Hare 1965; Vines 1968; Rego and Rigolot 1990) and similarly with diameter (Ryan and Frandsen 1991). Van Mantgem and Schwartz (2003) found bark thickness to be the primary determinant of cambial heat resistance, and larger-diameter trees (up to 20-cm diameter) resisted lethal heat to the cambium for longer periods of time.

The relationship between diameter or bark thickness and mortality is generally found to be negative (i.e. larger-diameter trees have lower probability of mortality). In some cases, however, it has been found that as tree size increases, so does the probability of mortality (Finney 1999; McHugh and Kolb 2003). This particular finding was following wildfires (as well as models in which wildfire and prescribed fire data were combined) in south-western ponderosa pine and may reflect longer heat residence times at the base of larger trees as a result of accumulating duff layers (Ryan and Frandsen 1991; Kolb *et al.* 2007) due to the absence of fire in the last several decades.

Bark thickness generally increases linearly with tree diameter (Ryan 1982*a*), even for smaller-diameter trees (van Mantgem and Schwartz 2003). However, studies estimating the allometric relationship of bark thickness and tree size (e.g. Adams and Jackson 1995) have indicated that a power function (i.e. quadratic polynomial) best describes the relationship between tree diameter and bark thickness. In contrast to crown-injury and fire-behaviour measurements, bark thickness and diameter relationships are extremely species-dependent. Thus, these more generalisable variables are a good complement to crown injury variables in predictive models and allow for a fine-tuning of model predictions for individual species (e.g. Ryan and Reinhardt 1988; Sieg *et al.* 2006).

Measurements of stem char (also referred to as bole and bark char) and stem scorch have been used ambiguously at times, and on occasion measurements labelled as char actually refer to scorch (e.g. Regelbrugge and Conard 1993). Fowler and Sieg (2004) also point out that bole scorch and bark char are often used interchangeably in the literature, and even in their review, they refer to bark char as both a measurement reflecting fire behaviour and a measurement indicative of injury to the cambium. A strict definition of bole scorch would be the amount of stem surface area or length that is noticeably contacted by heat or flame during a fire, whereas stem char is defined as the degree to which the bark is affected (i.e. consumed) by heat or flame, and is generally measured as a depth into the bark surface.

Bole char rating (Ryan 1982*b*) systems have been used as a surrogate to identify possible injury to the cambium from lethal heating. The relationship between measurements of bark char classification (light, moderate and heavy char) and cambial mortality has been investigated (Hood and Bentz 2007; Hood *et al.* 2007*d*). However, the findings from these studies are conflicting. In northern California, Hood *et al.* (2007*d*) suggest bark char can be accurate in predicting injury to cambial tissue, particularly at low and high bark char ratings. In a similar study in the northern Rockies, Hood and Bentz (2007) found bark char to be an unreliable predictor of cambium mortality, as suggested by Ryan (1982*b*). More recently, Hood *et al.* (2008) found that char codes were excellent predictors of mortality for thin-barked tree species (e.g. *Pinus contorta*, *P. albicaulis*, *Picea engelmannii*), but that deep charring was the most reliable predictor for thicker-barked species (e.g. *Pinus ponderosa*, *Pseudotsuga menziesii*). Cambium kill rating is extremely important in understanding fire effects on physiological function; however, it is not the most cost effective and efficient for managers to measure. Therefore, a surrogate variable for cambium mortality may be necessary.

The three different types of measurements of fire effects to tree stems (fire behaviour, tree resistance and degree of injury) all have strengths and weaknesses. For example, measuring a tree stem's resistance to heat injury is simple and has been shown to provide valuable information for prediction, whereas injury measurements give us a more explicit estimate of the mechanistic effect of fire on tree-level processes. As the field of post-fire tree mortality progresses, more research into relationships between these variables (e.g. bark char and cambium mortality) will be integral to understanding the underlying physiological response to heat injury from fire and the increased accuracy of post-fire predictions of tree mortality.

Fire severity, fire intensity, fuels and fire type

Measures such as fireline intensity and ground fire severity (i.e. amount of fuel consumption) have significant ramifications for mortality of trees following both prescribed and wildfire. Models that include ground severity (Sieg *et al.* 2006), fire intensity (Kobziar *et al.* 2006), fuel consumption (Finney and Martin 1993; Stephens and Finney 2002; Kobziar *et al.* 2006) and season of burn (Harrington 1993) have been developed for ponderosa pine, Douglas-fir, white fir, incense-cedar, sugar pine and redwood. However, these models have been developed mostly for mixed-conifer forests and for tree species associated with this forest type (i.e. white fir, incense-cedar, sugar pine, redwood).

A single study, following a large wildfire in south-western Oregon, has specifically examined overstorey and understorey fuel treatments as an explanatory variable in logistic mortality models (Raymond and Peterson 2005). Thinning without underburning showed increased rates of mortality, whereas the combination of these two treatments had the lowest rates of mortality. They also found treatment type to be a significant explanatory variable in one of their logistic regression models, although they did not report the accuracy of this particular model. Other studies have also found that thinning alone (Moghaddas and Craggs 2007; Ritchie *et al.* 2007; Safford *et al.* 2009), or in combination with underburning (Stephens and Moghaddas 2005; Ritchie *et al.* 2007), were effective treatments to reduce fire severity and post-fire tree mortality.

A wildfire study of ponderosa pine (Sieg *et al.* 2006) found that ground fire severity ratings following wildfire in ponderosa pine forests were significant in three logistic regression models. The remaining studies relating the effects of fire severity and intensity on individual post-fire tree mortality have followed prescribed burning (Finney and Martin 1993; Stephens and Finney 2002; Kobziar *et al.* 2006; Thies *et al.* 2006). Although many of these variables are difficult to measure following wildfires, methods exist to estimate fire intensity and behaviour variables. However, variables such as depth of duff or litter consumed (e.g. Finney and Martin 1993; Stephens and Finney 2002) that require pre-fire data, or direct measures of fire intensity such as flame height (Kobziar *et al.* 2006) are more practical in tree mortality models derived from prescribed fires. Ground severity ratings that categorise amounts of litter (none, low, moderate or high), duff and soil characteristics following fire (Ryan 1982*a*) are probably the most applicable to wildfire models where pre-fire data may not exist. Although these approximations of fire behaviour do not specify tree injury, they can be useful in predicting tree mortality (Raymond and Peterson 2005) and have been underutilised (Fig. 3).

Fire type (prescribed fire *v.* wildfire) has not been explicitly addressed by the majority of post-fire tree mortality studies, but is related to fire behaviour and effects measures such as intensity and severity. Fernandes *et al.* (2008) suggest that results from prescribed fire studies may or may not be applicable to higher-intensity fire behaviour that may occur in wildfires. However, the difference in post-fire mortality from prescribed fires and wildfires is only a reflection of different fire behaviour; thus, it seems likely that similar levels of tree injury resulting from prescribed burning or wildfire should result in similar levels of tree mortality.

The majority of existing models were developed from either prescribed or wildfires, and not both, resulting in a limited range of fire behaviour, intensity and subsequent severity. The number of studies of prescribed fire is larger than for wildfires (22 and 13 studies respectively), and these studies are focussed more heavily on ponderosa pine compared with the other 18 conifer species reviewed. Prescribed burning is still a widely used management tool; thus, recent research has continued to examine tree mortality from prescribed fires (e.g. Thies *et al.* 2005; Kobziar *et al.* 2006; Schwilk *et al.* 2006; Thies *et al.* 2006). This continued research is important for planning purposes as we re-introduce fire into large landscapes.

With the recent surge in wildfire activity across western coniferous forests, an increasing number of studies have occurred focussing on wildfires (e.g. Sieg *et al.* 2006; Hood and Bentz 2007; Hood *et al.* 2007*d*). Wildfire studies have almost exclusively focussed on Douglas-fir and ponderosa pine (Fig. 2), with the exception of incense-cedar, which has been modelled for post-wildfire mortality in two studies (Regelbrugge and Conard 1993; Hood *et al.* 2007*d*). McHugh and Kolb (2003) and McHugh *et al.* (2003) published the only post-fire tree mortality models developed from combined prescribed burn and wildfire data. Although these models were constructed for a limited scope (ponderosa pine in one prescribed fire and two wildfires), they indicate potential similarities between fire injury responses. Given the increased number of wildfires occurring in Oregon and Washington in the last decade, surprisingly little has been done to develop logistic regression models of post-wildfire Douglas-fir and ponderosa pine mortality in this region (Peterson and Arbaugh 1986; Raymond and Peterson 2005).

Over the last two decades, few studies have used both wildfire and prescribed burn data to evaluate a predictive model (Hood *et al.* 2007*a*), examined a prescribed fire model with wildfire data (Weatherby *et al.* 1994), or developed models using both prescribed and wildfire data (McHugh and Kolb 2003, McHugh *et al.* 2003; Breece *et al.* 2008). Additional research, focussing on models developed from both prescribed and wildfires, is needed to further understand injury effects on post-fire tree mortality from a range of fire behaviour and severity. Moreover, it would be useful to apply tree mortality data from both fire types to validate existing models along a wide gradient of fire behaviour and severity.

Season of burn

Throughout the fire ecology literature, there is a great deal of discussion and little consensus about the effects of season of burn on the post-fire environment (Harrington 1987, 1993; Perrakis and Agee 2006). Three studies have tested season of burn as a tree mortality explanatory variable in a logistic regression model (Ryan *et al.* 1988; Harrington 1993; Thies *et al.* 2006). Only one of these found it to be statistically significant (Harrington 1993), whereas others have found no attributable effect of season on tree mortality following prescribed burns (Schwilk *et al.* 2006) or wildfires (Sieg *et al.* 2006).

A general pattern of increased mortality in spring burns has been noted by both Ryan *et al.*(1988) and Swezy and Agee (1991), whereas others have found no attributable effect of season on tree mortality following prescribed burns (Schwilk *et al.* 2006; Thies *et al.* 2006) or wildfires (Sieg *et al.* 2006). The increased mortality in spring may be attributed to several factors, the most likely being bud phenology at the time of burning (Wagener 1961; Dietrich 1979; Harrington 1987). In late spring and early summer, bud development and active growth may increase the susceptibility of these tissues to injury, specifically for species such as ponderosa pine (Wagener 1961; Wyant and Zimmerman 1983; Harrington 1987; Swezy and Agee 1991). Warmer temperatures during spring burns in some areas may require less heating to induce tissue injury to stems and buds (Harrington 1987). However, high temperatures can exist in the autumn as well, and similar injury could occur under these conditions.

It is likely that a combination of these factors as well as moisture-related stress contribute to seasonal effects of tree mortality following fire. Variables that specify stages of bud development during fire may be more effective, and in combination with ambient temperature and moisture measurements, may capture the interannual and seasonal variability of the underlying processes that are not adequately represented by season of burn alone. Ryan *et al.* (1988) point out that we need to separate effects of fire behaviour and tree susceptibility. Fire behaviour is often not adequately quantified and may differ among seasons of burn, as well as between different burns occurring in the same season. Season of burn as a categorical variable reflects both fire behaviour and tree susceptibility, and thus alone does not seem to consistently increase accuracy or fit of logistic regression models for post-fire mortality predictions. There is a broader need to understand and investigate the physiological state of the tree, as well as the environmental factors that vary with season. To date, research has not shown that season of burn integrates these factors adequately.

Insects and pathogens

Insects and pathogens can have a significant effect on tree survival following fire (Miller and Patterson 1927; Geiszler *et al.* 1980; Littke and Gara 1986; Thomas and Agee 1986; Ryan and Amman 1994; Maloney *et al.* 2008). However, only nine studies (six wildfires and three prescribed burns; Fig. 3) attempted to use a measure of insects as a possible predictor. It was only statistically significant in five of these studies. Only three studies have targeted a pathogen (dwarf mistletoe – *Arceuthobium spp.*) as a possible predictor of post-prescribed fire tree mortality (Harrington and Hawksworth 1990; Conklin and Geils 2008; Maloney *et al.* 2008).

The role of insects in tree mortality (second-order effect) following large disturbances such as fire, and the interaction of these two disturbance agents (McCullough *et al.* 1998) is not well understood and has continued to be a topic of research (Ryan and Amman 1994; McHugh and Kolb 2003; Wallin *et al.* 2003; Hood and Bentz 2007; Breece *et al.* 2008). Bark beetles are likely to be the most significant additional mortality cause or cause of further tree injury following fire. The most common measure of this effect is simply documenting the presence of bark beetles on a tree following fire. Some studies have also inspected a section of bark from dead trees to determine attack success and species present. More recently, attack ratings have been used to document the degree of presence of subcortical insects (McHugh and Kolb 2003; Breece *et al.* 2008), whereas others have used the percentage circumference of the tree stem attacked by a particular species or group of species (Hood and Bentz 2007; Hood *et al.* 2007*b*).

The use of insect attack as a post-fire tree mortality explanatory variable has been investigated in several regions of the western USA, including the Rocky Mountains, the south-west, northern California, the Cascades of Oregon and Washington, and the Black Hills of South Dakota. *Ips* and *Dendroctonus* are the most commonly studied genera of subcortical insects in relation to predicting post-fire tree mortality. This is not surprising given their major hosts are ponderosa pine and Douglas-fir, the most frequently studied tree species in post-fire tree mortality. Other bark beetles examined include the red turpentine beetle (*Dendroctonus valens*) and ambrosia beetles (*Gnathotricus*, *Treptoplatypus*, *Trypodendron*, *Xyleborus*).

Peterson and Arbaugh (1986) in a study in the northern Rockies found insect attack (none, low, medium, high – based on the number of observable entrance holes in the tree stem) statistically significant in a post-fire logistic regression model. A similar study by the same authors (Peterson and Arbaugh 1989) in the Cascades of Washington and Oregon did not find statistically significant effects of insect attacks. Climatic differences in these regions and stress on trees from drought may be factors associated with this difference. McHugh *et al.* (2003) developed a model to specifically examine relationships of crown injury and insect attack rating, but had previously found insect attack insignificant when several other variables were included (McHugh and Kolb 2003). In a more spatially extensive study (northern Arizona, north-eastern Colorado, south-western Montana and western South Dakota), the presence (no quantification) of *Ips* was statistically significant in a logistic regression model across all sites, but was defined as a 'tailoring' variable that slightly increased classification accuracy (Sieg *et al.* 2006).

When applying logistic regression models that include an insect attack predictor to post-fire management scenarios, or for model validation efforts, the species of bark beetle may be different between the model and the post-fire scenario. The following questions need to be answered for future model applications. Do similar bark beetle species and varying levels of their presence create similar disruptions of physiological pathways in trees following fire? Many bark beetles (e.g. *Dendroctonus ponderosae*) carry fungi into tree's sapwood and further inhibit sapflow, and these may be more likely to increase mortality following injury from fire. Is the difference in bark beetle presence appreciable given the predictive models use additional injury and fire behaviour variables? Are bark beetles more important contributors to mortality with higher levels of other injury such as crown scorch, as seen by Wallin *et al.* (2003)? Would a simple generalised insect attack rating (regardless of insect and host species) be adequate to help predict post-fire tree mortality? More general insect attack ratings, possibly combined with measures of tree vigour, may improve post-fire predictions, as well as allow comparisons among future research.

Pathogens and their presence on trees have largely been ignored as possible predictors of delayed tree mortality following fire. With the exception of dwarf mistletoe on ponderosa pine in New Mexico (Conklin and Geils 2008) and north-western Arizona (Harrington and Hawksworth 1990), no work has been undertaken to examine the role of other pathogens (e.g. root rots, fungal evidence of heart rot) in tree mortality. Interestingly, both studies of dwarf mistletoe occurred in prescribed burns that had an emphasis on sanitation of the pathogen. Harrington and Hawksworth (1990) concluded that trees surviving a prescribed fire had a much lower Dwarf Mistletoe Rating (DMR; Hawksworth 1977) than trees that died, and that trees with higher DMR ratings generally had higher levels of crown scorch. They also reported DMR as a significant predictor of mortality in conjunction with tree diameter and crown length scorch class. More recently, Conklin and Geils (2008) found less of a relationship between crown scorch and average DMR rating, but did indicate that at high levels of scorch (>90%) combined with high DMR ratings (5–6), dwarf mistletoe was important in tree mortality prediction.

Given the role of insects in widespread tree mortality (Raffa *et al.* 2008) and tree stressors such as drought, the future importance of insect attack and pathogen occurrence on remaining live trees may become a more important research topic. Given the small amount of work to date, much more research on insects and pathogens in relation to post-fire tree mortality is warranted.

Tree vigour and predisposition to mortality

One of the more overlooked groups of variables in post-fire tree mortality models is those variables that quantify the degree to which trees are predisposed to die (Waring 1987; Filip *et al.* 2007), or describe stand characteristics that can affect overall tree vigour (Swezy and Agee 1991). Few examples of these exist in currently developed mortality models, but they include measures such as pre-fire growth rate (van Mantgem *et al.* 2003) and pre-fire live crown proportion (Sieg *et al.* 2006; Thies *et al.* 2006). However, there has been little attempt to incorporate measures of predisposition such as stand density, which may indicate stress and higher probability of insect attack (Waring and Pittman 1985), or tree vigour classes (Keen 1943; Swezy and Agee 1991).

Many of these variables can be easily measured in the field (e.g. canopy position, live crown, stand density) and readily used in simplistic models for activities such as salvage logging. Factors such as stand density also play a role in potential fire behaviour and thus tree mortality following fire. Others aren't as

Table 3. Knowledge gaps and areas of emphasis for future research in post-fire tree mortality prediction and application

Topic	Research needs
Model validation and scope	Increased sample sizes from larger studies; meta-analyses using datasets from multiple regions; length of delayed mortality using background mortality comparisons
Crown and stem damage variables	Consistent definitions and measurements; physiological mechanisms contributing to delayed tree mortality
Tree injury and physiology	Development of a better mechanistic understanding of the physiological response of trees to injuries such as cambium and crown mortality. Expansion of current understanding of bark characteristics through continued research and synthesis of previous research. Development of a non-destructive measure of cambium mortality
Tree vigour and predisposition to mortality	More expansive testing of variables that indicate tree and stand vigour and possible predisposition to mortality
Tree mortality process models	Further development of process-based fire behaviour and mortality models based on physical mechanisms of resulting tree injury
Management applications	Linking of research and management through development and validation of field guides to predict post-fire tree mortality; updating of fire effects models with more specific regional or species-level data
Insects and pathogens	Explicit studies focussing on the role of insects, pathogens and their interactions post fire and the influence on delayed tree mortality; wider array of tree species affected by bark beetle attack; examination of attack rating methods
Season of burn	Well-replicated studies specifically testing season of burn in both prescribed burning and wildfires
Ground severity, fire intensity and fuels	Effects of fuel loads, fuel consumption and fuels treatments; linking of litter and duff consumption to damage below ground to roots
Geographic regions	Insufficient data and models for Oregon and Washington, Klamath region of northern CA, South-west
Tree species	Broader range of tree species, including less-abundant species associated with mixed conifer as well as western larch

quickly quantified (e.g. pre-fire growth rate, Palmer Drought Severity Index) in the field and may be more useful in larger models that may incorporate direct physiological relationships with fire injury and mortality.

Management applications

As models are developed for, or applied to, management scenarios, the objectives need to be considered. The most useful models for on-the-ground field applications (e.g. salvage marking) are ones that contain the fewest, most easily observed explanatory variables, and these are typically derived from simple logistic regression models. Alternatively, during planning of prescribed burning treatments or post-wildfire restoration, a predictive tool for tree mortality based on fire behaviour, tree injury and physiological response may be more appropriate.

Several examples exist in which post-fire tree mortality regression models, or information taken from those models, have been used in a management context. One of the earliest examples was the development of Nomograms by Reinhardt and Ryan (1988) using models they developed from prescribed fires. More recently, Thies *et al.* (2008) developed a 'mortality-probability calculator' based on the proportion of bole scorch and crown scorch to predict tree mortality in prescribed and wildfires in eastern Oregon. Prior to this, Scott *et al.* (2002) developed step-by-step field guidelines for assessing tree injury and mortality following fire in the Blue Mountains of Oregon. In essence, the Scott Guidelines are a rating system that assigns a ranking (0, 1, 2, 3, etc.) for factors known to be important mortality predictors, such as crown volume scorch, bole scorch, duff consumption and several other factors.

The most frequent and widespread use of post-fire tree mortality logistic regression models by land managers is in larger fire-effects and forest management planning software such as FOFEM, FFE-FVS and Behave-Plus. These complex models incorporate selected regression models for post-fire tree mortality, and are used to identify ecosystem effects and vegetative structural changes following both prescribed burning and wildfires (Reinhardt *et al.* 1997; Reinhardt and Crookston 2003; Andrews *et al.* 2008). These programs and the supplementary tree mortality logistic regression models have proved useful in evaluating fuels treatments (Christensen *et al.* 2002), managing bark beetle infestations (see Reinhardt and Crookston 2003) and producing inputs for fire spread and fuel consumption models such as FARSITE (Finney 1999), as well as determining effects on other ecosystem components.

The predictive tree mortality logistic regression model used in all three of these fire behaviour and effects programs was developed originally by Ryan and Reinhardt (1988) and updated by Ryan and Amman (1994), and more recently by Hood *et al.* (2008) using more data from both wildfire and prescribed burns across a larger geographic scope and set of species that used species-level equations to predict tree mortality (FOFEM v. 5.9). Although the original model is a widely used silvicultural tool in the western USA (Hood *et al.* 2007*a*), it was initially developed from prescribed fires and, until recently, has received little validation (Weatherby *et al.* 1994; Hood *et al.* 2007*a*).

Future research needs

Several areas of future research in tree mortality modelling need to be addressed for the field to continue to move forward

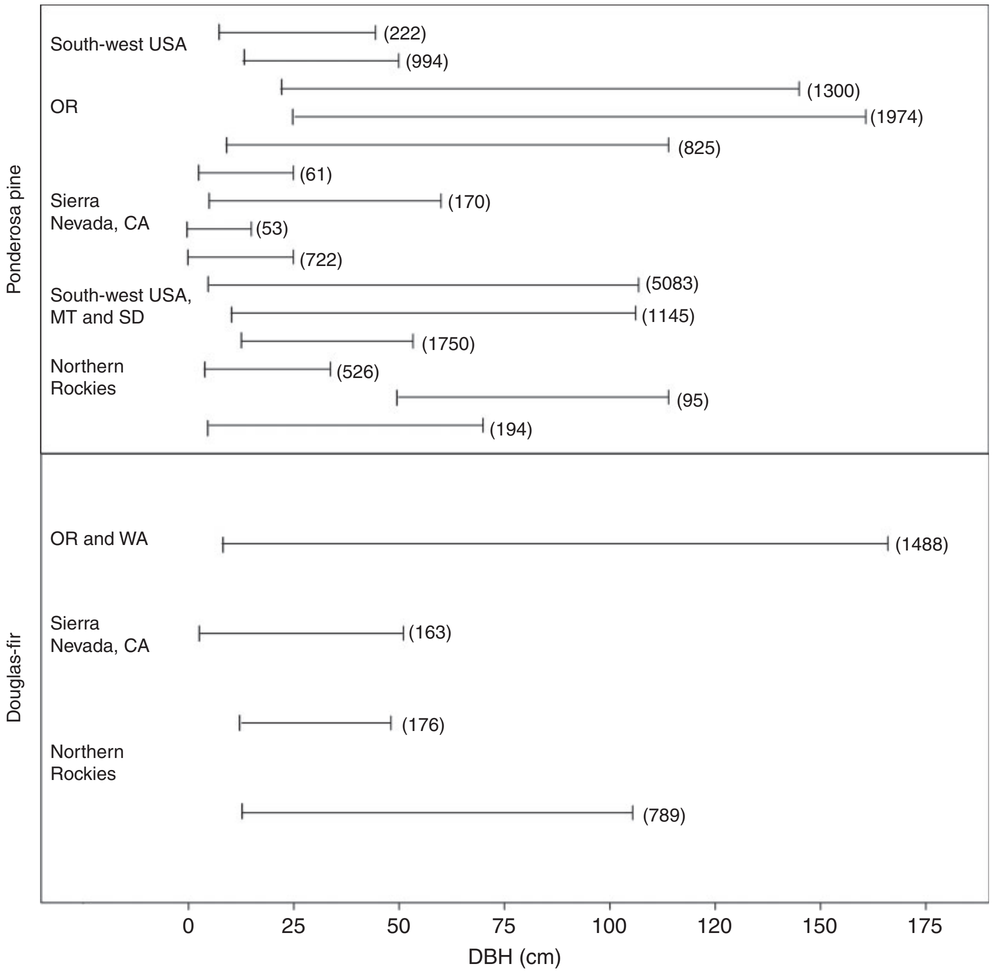

Fig. 4. Range in reported DBH (diameter at breast height) distributions for post-fire tree-mortality logistic regression modelling studies of Douglas-fir and ponderosa pine in western North America. Sample sizes are in parentheses.

(Table 3). In particular, large meta-analyses focussed on validation and limitations of logistic regression models are necessary. Larger sets of data including multiple species, geographic regions and climatic regimes, and across a large range of fire types and fire behaviour measures, need to be applied to previously built models. For example, if all the data in Fig. 4 were used to validate and develop more general models for Douglas-fir and ponderosa pine, the applicability of these models would be much broader and undoubtedly more accurate. If warranted by validation results, these datasets could also be used to create new models using a larger suite of possible variables as discussed above (e.g. insects and pathogens, fuel consumption, tree and stand vigour estimates). In addition, using more rigorous model selection techniques (see Model Development and Model Evaluation sections) will improve future modelling endeavours.

Logistic models that predict post-fire tree mortality are limited because they don't explain mechanistically the link between fire behaviour, tree injury and subsequent mortality (Michaletz and Johnson 2008). Physical processes underlying fire and heat transfer, tree injury and mortality need to be further examined using previous work (e.g. Dickinson and Johnson 2004; Michaletz and Johnson 2006, 2008) as a foundation. A better understanding of the underlying physiological response of various tree components (i.e. roots, stems, foliage) following tree injury (Waring 1987; Filip *et al.* 2007) from fire is a necessary step to move forward with biophysical process models (Kavanagh *et al.* 2010).

An enhanced ability to model underlying biophysical and physiological processes, combined with validation of empirically based logistic regression models, will create the potential to link simplistic logistic regression models and more complex process-based models. As suggested by Butler and Dickinson (2010), larger fire behaviour and ecosystem effects models provide an appropriate platform for this endeavour. As more of this research is accomplished, validation and analysis of limitations need to be tested using appropriate field data across a range of tree species with differing physical properties of bark, buds and allometry (Michaletz and Johnson 2008).

Conclusions

This review provides a foundation for future research and application by assembling the considerable amount of research that has examined post-fire tree mortality logistic modelling, and the more than 100 logistic regression models that have been developed following prescribed burning or wildfire. The results of this review specify what logistic models have provided, concerns that need to be addressed and future research that is needed for the field to move forward.

Logistic regression models have utilised a variety of explanatory variables that reflect fire behaviour and fire injury. However, crown injury variables have been repeatedly documented as the most significant post-fire tree mortality explanatory variables. Often a crown injury variable in combination with a measurement of stem injury (e.g. bark char) or fire behaviour (e.g. scorch height) on the tree stem is found to produce the best predictions of post-fire mortality.

Continued development of new logistic models on limited datasets using the same or similar variables may not be beneficial because the use of this suite of variables is already well understood (Fowler and Sieg 2004; Sieg *et al.* 2006) and there is an ensuing need to validate the models over broader scopes. More emphasis should be placed on evaluation of variables that indicate physiological status of tree components. In addition, variables such as season of burn, fuel consumption, indicators of tree vigour, and effects of insects and pathogens have not been examined thoroughly and warrant more attention.

However, the lack of consistent definitions and application of fire behaviour and tree injury variables has hindered the further development and use of post-fire tree mortality logistic models. We suggest that consistent measurement and use of explanatory variables will aid in future model comparisons and management applications. Similarly, more complete characterisation of study areas and other factors influencing model scope (e.g. fire size and severity, range of tree diameter, sample sizes, estimated variances) in the future will extend the usefulness of future research.

Further exploration of physiological-based variables, a better understanding of the biophysical mechanisms behind fire behaviour (e.g. heat transfer and tissue injury) and the relationships between these and tree mortality are crucial to improved modelling of post-fire tree mortality. The development and linkage of mechanistic models to empirically based statistical models through larger modelling frameworks would further our knowledge and ability to predict post-fire tree mortality processes, and apply this knowledge in post-fire management.

We question whether building additional models for Douglas-fir and ponderosa pine without first validating existing models is appropriate. Understanding current model use and applicability by systematic validation of previously built logistic models will be beneficial. Specifically, we recommend validation of previously built models that have larger sample sizes and spatial scope, were developed from at least 3 years of post-fire tree mortality data, and used rigorous modelling methodologies. Region-to-region model applicability has shown some feasibility but needs more attention through larger meta-analyses and validation. Interestingly, with over 100 logistic regression models published for conifers in the west, only one model (Ryan and Amman 1994) is being used for pre- and post-fire (prescribed and wildfire) management planning by federal agencies using FOFEM, FFE-FVS and Behave-Plus. As more models are built with larger sample sizes and more work is done in the area of validation, attention needs to be paid to linking current research and model development with management applications.

Acknowledgements

Funding for this project was provided by the Western Wildland Environmental Threat Assessment Center, US Forest Service Pacific Northwest Research Station (Joint Venture Agreement number PNW 07-JV-11261900–075). Collaborative contributions for the direction of the project and multiple reviews of the manuscript were provided by Charles 'Terry' G. Shaw. We also appreciate the feedback of several anonymous reviewers and the Associate Editor, which undoubtedly improved the quality of the manuscript.

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Appendix

Table A1. Characteristics regarding scope of inference of post-fire prescribed burning models to predict tree mortality

Study area refers to the area represented by sample plots. Species codes are as listed in Appendix 5. DBH, diameter at breast height; NR, not reported in publication

Study code Author(s) (year)	*n* years post fire (model basis)	Study area (ha)	*n* fires	*n* sites	*n* plots sampled	Sample plot size	Total *n* trees	Model type(s)	Variables tested	Replicated	Validated
1A											
Bevins (1980)	1 year	NR	NR	19	NR	NR	176	Logistic	DBH Crown scorch height % live crown scorched	No	No
1B											
Ryan and Reinhardt (1988)	4 years	NR	43	43	NR	0.7–9.0 ha	2356	Logistic	DBH Tree height Bark thickness Scorch height % crown killed	No	No
1C											
Wyant *et al.* (1986)	2 years	3.8 ha	1	1	1	3.8 ha	198	Discriminant analysis ANOVA	DBH Tree height Pre-fire live crown length % live crown length scorch (four quadrants) % live crown length consumption (four quadrants) Stem char (four quadrants) Maximum crown scorch height	No	Yes (secondary species)
1D											
Ryan *et al.* (1988)	8 years	NR	20	20	20[A]	NR	166	Logistic ANOVA	DBH Scorch height Crown scorch Number of dead cambium quadrants Season of burn	No	No
1E											
Harrington and Hawksworth (1990)	1 year	NR	1	1	NR	NR	191	Logistic	Crown scorch class Dwarf mistletoe rating Bole char rating	No	No

1F											
Saveland and Neuenschwander (1990)	6 months	NR	NR	NR	NR	NR	194	Logistic	DBH Scorch height Crown scorch	No	No
1G											
Finney and Martin (1993)	1 year	NR	2	2	32	0.09–0.25 ha	512	Logistic	DBH % crown volume scorched Flame height Flame length Duff consumption (tree- or plot-based)	No	No
1H											
Harrington (1993)	10 years	NR	6	1	18	1.0 ha	526	Logistic	DBH class % crown scorch Season	Yes	No
1I											
Mutch and Parsons (1998)	5 years	2	1	1	2	1.0 ha	773	Logistic	DBH % crown volume scorched	No	No
1J											
Stephens and Finney (2002)	2 years	2	1	1	2	1.0 ha	1025	Logistic	DBH Duff consumption % crown volume scorched Scorch height	No	No
1K											
McHugh and Kolb (2003)	3 years	23.8	1	1	16	0.04 ha	222	Logistic	DBH Height % live crown ratio Crown position % crown scorched % crown consumption Total crown damage Bole char – leeward Bole char – windward Bole char severity – leeward Bole char severity – windward Ground char severity Insect attack rating Weather damage Logging damage Soil disturbance	No	No

(*Continued*)

Table A1. (Continued)

Study code Author(s) (year)	*n* years post fire (model basis)	Study area (ha)	*n* fires	*n* sites	*n* plots sampled	Sample plot size	Total *n* trees	Model type(s)	Variables tested	Replicated	Validated
1L McHugh *et al.* (2003)	3 years	23.8	1	1	16	0.04 ha	222	Logistic	DBH % crown scorched % crown consumption Total crown damage Insect attack rating	No	No
1M van Mantgem *et al.* (2003)	5 years	14	1	1	2	1.1 and 1.0 ha	2622	Logistic	DBH Pre-burn average annual growth rate % crown volume scorched	No	Yes
1N van Mantgem and Schwartz (2004)	2 years	NR	1	1	1	NR	53[B]	Logistic	Bark thickness Crown scorch class Stem scorch height	No	No
1O Thies *et al.* (2006)	4 years	79.1	2	4	72	0.2 ha	3415	Logistic ANOVA	DBH Height Live crown proportion Needle scorch proportion Bud kill proportion Ground char severity (1–4) Basal char severity (1–4) Basal char minimum Bole scorch proportion Season	Yes	No
1P Schwilk *et al.* (2006)	2 years	400	6	1	60	0.1 ha	NR	Logistic ANOVA	DBH Crown length scorched Bole char height	Yes	No

1Q											
Kobziar *et al.* (2006)	8 months	1780	3	1	60	0.04 ha	1294	Logistic	DBH Bark char height Bark char severity (1–3) % bole char below DBH Scorch height % crown volume scorched % crown volume consumed Total crown damage Fireline intensity % duff consumption	Yes (ABCO)	No
1R											
Breece *et al.* (2008)	3 years	396 405 247 262	4	4	25–40 per site	0.03 ha	994	Logistic	Live crown ratio Total crown damage Crown scorch Crown consumption Leeward bole char height Windward bole char height Bole char severity Bark beetle attack rating	Yes	Yes[C]
1S											
Hood *et al.* (2007*a*)	3 years	NR	21	NR	NR	NR	14 803	Logistic	Bark thickness Crown volume scorched	Yes	Yes[D]
1T											
Conklin and Geils (2008)	3 years	~480	6	2	14	NR	1585	Logistic Proportional hazards model	DBH Crown scorch length Bole char rating Dwarf mistletoe rating	Yes	No

[A]Eleven plots sampled in early-season fire(s), nine plots sampled in late-season fire(s).
[B]Trees modelled had 5.0 cm basal bark removed before burn treatments.
[C]Validation of previous mortality models (McHugh and Kolb 2003; McHugh *et al.* 2003) using data collected from current study.
[D]Validation of Ryan and Amman (1994) model using collected data from 21 wild and prescribed fires across a wide geographic range. Validation was replicated for two or more fires for lodgepole pine, Engelmann spruce, subalpine fir, yellow pine (ponderosa and Jeffrey) and Douglas-fir.

Table A2. Characteristics regarding scope of inference of post-fire wildfire models to predict tree mortality

Study area refers to the area represented by sample plots. Species codes are as listed in Appendix 5. DBH, diameter at breast height; NR, not reported in publication

Study code Author(s) (year)	*n* years post-fire (model basis)	Study area (ha)	*n* fires	*n* sites	*n* plots sampled	Sample plot size	Total *n* trees	Model type	Variables tested	Replicated	Validated
2A Peterson and Arbaugh (1986)	2 years	NR	9	9	NR	Point-centred quarter method on transects (4 trees per point)	302 (PSME) 243 (PICO)	Logistic discriminant analysis	DBH Bole length Crown ratio Crown diameter Crown scorch Bark thickness Basal scorch (% circumference) Bark char (depth) Bark char ratio (depth char/depth bark) Insect (low, medium, high based on *n* of entries)	No	No
2B Peterson and Arbaugh (1989)	2 years	NR	4	4	NR	Point-centred quarter method on transects (4 trees per point)	294	Logistic	DBH Tree height Crown ratio Bark thickness Scorch height Crown scorch (%) Basal scorch (%) Upslope bark char Downslope bark char Bark char ratio Live cambium (four quadrants) Insect (low, medium, high based on *n* of entries) Site	No	No
2C Regelbrugge and Conard (1993)	2 years	NR	1	25	75	400 m^2	1275	Logistic	DBH Height Height stem bark char Relative char height (proportion of tree height)	No	Yes[A]
2D Borchert *et al.* (2002)	3 years	NR	1	13 (9 PICO3) (4 PISA)	13	NR	263	Logistic	DBH Tree height % crown scorched Height of bole bark char	No	No

2E											
McHugh and Kolb (2003)	3 years	80 6475	2	2	46 and 75 25	0.04 and 0.08 ha 18 ha (NR) 7–20 m-width transects	312 and 833	Logistic	DBH Height % live crown ratio Crown position % crown scorched % crown consumption Total crown damage Bole char – leeward Bole char – windward Bole char severity – leeward Bole char severity – windward Ground char severity Insect rating Weather damage Logging damage Soil disturbance	No	No
2F											
McHugh *et al.* (2003)	3 years	80 6475	3	3	46 and 75 25	0.04 and 0.08 ha 18 ha (NR) 7–20 m-width transects	312 833	Logistic	DBH % crown scorched % crown consumption Total crown damage Insect rating	No	No
2G											
Raymond and Peterson (2005)	2 years	NR	1	2	5	18 × 18 m	244	Logistic	DBH % crown volume scorch Crown scorch height *n* dead cambium samples Treatment (thinned or thinned and underburned)	No	No
2H											
Sieg *et al.* (2006)	3 years	NR	5[B]	5	9–12 per site	10 × 200-m belt transects	5083	Logistic	DBH Height Pre-fire live crown ratio % crown scorch volume % crown consumption volume Total crown damage % basal circumference scorch Height to live branch Crown scorch height Crown consumption height Maximum bole scorch height Minimum bole scorch height Ground fire severity rating (0–4) Bark beetle presence	Yes	Yes

(*Continued*)

Table A2. (Continued)

Study code Author(s) (year)	*n* years post-fire (model basis)	Study area (ha)	*n* fires	*n* sites	*n* plots sampled	Sample plot size	Total *n* trees	Model type	Variables tested	Replicated	Validated
2I											
Keyser *et al.* (2006)	5 years	NR	1	18	3 per site	0.3 ha	963	Logistic	DBH Bark thickness Height Pre-fire crown base Maximum scorch height % bole char % live crown length scorched Site	No	Yes[A]
2J											
Hood *et al.* (2007*d*)	2–4 years (dependent on species)	NR	5	5	NR	NR	5246	Logistic	DBH % crown length killed Cambium kill rating Ambrosia beetle presence Red turpentine beetle presence Bark char classification	No	No
2K											
Hood and Bentz (2007)	4 years	23 876 28 733 1827	3	3	4 51 28	0.08 ha 0.04 ha 0.04 ha	118 453 218	Logistic	DBH % crown volume scorched Crown kill rating Ground char index Beetle attack	Yes	Yes[B]
2L											
Hanson and North (2009)	3–4 years (dependent on species)	80	2	2	NR	NR	411	Logistic	DBH % crown volume killed % crown volume scorched % crown consumption (of tree height) Bole char		
2M											
Hood *et al.* (2010)	5 years	NR	5	NR	NR	NR	5677	Logistic	DBH % crown volume killed Crown length scorched % crown volume scorched Cambium kill rating Post-fire beetle attack	No	No

[A]Validation using randomly selected 25% of trees not used in model calibration.
[B]Three fires used for model calibration, two used for model validation.

Table A3. Prescribed burning post-fire tree mortality models including tree species modelled, sample size, variable coefficients, modelling procedures, ROC curve and accuracy values

Species and variable codes are as listed in Appendix 5. Numbers in parentheses below models indicate standard errors of coefficients if reported. NR, not reported in publication. Validation Receiver Operating Characteristics (ROC) (*C*) and accuracy values represent individual fires and all fires combined. Individual fires values represent smaller sample sizes. When considering validation accuracy for Hood *et al.* (2007*a*) (1S), stand-level mortality as calculated by Predicted – Observed (%): positive values equate to overprediction of mortality, whereas negative values represent underprediction. Validation of previously built model (Ryan and Amman 1994). NA, not applicable

Study code Author(s) (year)	Species	Sample size	Model	Accuracy (criteria)	ROC curve value (*C*)	Validation accuracy (criteria)
1A						
Bevins (1980)	PSME	176	$P_s = 1 + \exp[(0.1688 - 0.3174\text{DBH} + 0.09321\text{SH})]$[A]	NR	NA	NA
1B						
Ryan and Reinhardt (1988)	All	2356	$P_m = 1/1 + \exp[(-1.466 + 1.190\text{BT} - 0.1775\text{BT}^2 - 0.000541\text{CK}^2)]$ (0.1357) (0.1163) (0.0179) (0.000039)	0.51–0.86[B] (0.5)	NA	NA
	PSME	1488	$P_m = 1/1 + \exp[(-0.9245 + 1.0589\text{PSME} + 0.9407\text{BT} - 0.0690\text{BT}^2 - 0.000542\text{CK}^2)]$ (0.1955) (0.1414) (0.1955) (0.0273) (0.000040)	0.86 (0.5)	NA	NA
	LAOC	287	$P_m = 1/1 + \exp[(-0.9245 + 1.5475\text{LAOC} + 0.9407\text{BT} - 0.0690\text{BT}^2 - 0.000542\text{CK}^2)]$ (0.1955) (0.2116) (0.1955) (0.0273) (0.000040)	0.88 (0.5)	NA	NA
	PIEN	96	$P_m = 1/1 + \exp[(-0.9245 - 1.495\text{PIEN} + 0.9407\text{BT} - 0.0690\text{BT}^2 - 0.000542\text{CK}^2)]$ (0.1955) (0.2895) (0.1955) (0.0273) (0.000040)	0.88 (0.5)	NA	NA
	PICO	144	$P_m = 1/1 + \exp[(-0.9245 - 0.1472\text{PICO} + 0.9407\text{BT} - 0.0690\text{BT}^2 - 0.000542\text{CK}^2)]$ (0.1955) (0.2350) (0.1955) (0.0273) (0.000040)	0.88 (0.5)	NA	NA
	ABLA	172	$P_m = 1/1 + \exp[(-0.9245 - 1.1269\text{ABLA} + 0.9407\text{BT} - 0.0690\text{BT}^2 - 0.000542\text{CK}^2)]$ (0.1955) (0.2363) (0.1955) (0.0273) (0.000040)	0.86 (0.5)	NA	NA
	THPL	69	$P_m = 1/1 + \exp[(-0.9245 + 0.8860\text{THPL} + 0.9407\text{BT} - 0.0690\text{BT}^2 - 0.000542\text{CK}^2)]$ (0.1955) (0.3697) (0.1955) (0.0273) (0.000040)	0.87 (0.5)	NA	NA
	TSHE	100	$P_m = 1/1 + \exp[(-0.9245 - 0.7231\text{TSHE} + 0.9407\text{BT} - 0.0690\text{BT}^2 - 0.000542\text{CK}^2)]$ (0.1955) (0.3060) (0.1955) (0.0273) (0.000040)	0.89 (0.5)	NA	NA
1C						
Wyant *et al.* (1986)	PSME	103	NA	87% (NA)[C]	NA	86% (PSME)
	PIPO	95	NA	87% (NA)[C]	NA	84% (PIPO)
1D						
Ryan *et al.* (1988)	PSME Univariate	166	$P_m = 1/1 + \exp[-(-1.694 + 1.263\text{NDEAD})]$	80% (0.5)	NA	NA
	PSME Multivariate		$P_m = 1/1 + \exp[-(0.392 - 0.099\text{DBH} + 1.275\text{NDEAD})]$	83% (0.5)	NA	NA
1E						
Harrington and Hawksworth (1990)	PIPO	191	$P_s = 1/1 + \exp[(4.91 + 0.10\text{DBH} - 0.10\text{CS} - 0.29\text{DMR})]$	92% (0.5)	NA	NA

(*Continued*)

Table A3. (Continued)

Study code Author(s) (year)	Species	Sample size	Model	Accuracy (criteria)	ROC curve value (C)	Validation accuracy (criteria)
1F						
Saveland and Neuenschwander (1990)	PIPO	194	$P_m = 1/1 + \exp[-(-2.33 + 0.37\text{DBH} - 0.36\text{SH})]$	NR	0.85	NA
1G						
Finney and Martin (1993)	SESE3	512	$P_{tk} = 1/(1 + \exp[(-2.293 + 0.483\text{DBH} - 0.504\text{FL} - 0.026\text{UDWC})]^{\text{D}}$ (0.327) (0.054) (0.197) (0.004)	NR	NR	NA
			$P_{tk} = 1/(1 + \exp[(0.371\text{DBH} - 2.645\text{FCVS} - 0.169\text{UDDC})]^{\text{D}}$ (0.036) (0.268) (0.030)	NR	NR	NA
			$P_{tk} = 1/(1 + \exp[(-0.925 + 0.357\text{DBH} - 0.863\text{FL} - 0.047\text{FC})]^{\text{E}}$ (0.229) (0.016) (0.094) (0.005)	NR	NR	NA
			$P_{tk} = 1/(1 + \exp[(-0.772 + 0.360\text{DBH} - 0.083\text{SH} - 0.050\text{FC})]$ (0.241) (0.017) (0.010) (0.005)	NR	NR	NA
1H						
Harrington (1993)	PIPO	526 (total) 180 (spring) 162 (summer) 184 (autumn)	$P_m = 1/1 + \exp[(-1.16 + 1.04\text{S} + 1.94\text{L} + 0.12\text{H} + 0.14\text{D})]$	87%	NA (−0.5)	NA
1I						
Mutch and Parsons (1998)	ABCO	689	$P_m = 1/1 + \exp[-(-1.4197 + 0.0524\text{PCVS} - 0.141\text{DBH})]$	NR	NA	NA
	PILA	84	$P_m = 1/1 + \exp[-(-1.152 + 0.1074\text{PCVS})]$	NR	NA	NA
1J						
Stephens and Finney (2002)	ABCO	400	$P_m = 1/1 + \exp[-(-7.0117 - 0.0659\text{DBH} + 0.1061\text{PCVS} + 0.00488\text{DUFF})]$	NR	0.968	NA
			$P_m = 1/1 + \exp[-(-6.2674 - 0.0503\text{DBH} + 0.1031\text{PCVS})]$	NR	0.958	NA
	CADE27	110	$P_m = 1/1 + \exp[-(-12.0408 - 0.061\text{DBH} + 0.1554\text{PCVS})]$	NR	0.958	NA
			$P_m = 1/1 + \exp[-(1.2721 - 0.1492\text{DBH} + 0.3373\text{SCHT})]$	NR	0.77	NA
	PILA	140	$P_m = 1/1 + \exp[-(-11.241 + 0.146\text{PCVS})]$	NR	0.979	NA
			$P_m = 1/1 + \exp[-(-0.2084\text{DBH} + 0.3870\text{SCHT} + 0.0154\text{DUFF})]$	NR	0.808	NA
	PIPO	170	$P_m = 1/1 + \exp[-(-6.5866 - 0.0812\text{DBH} + 0.0836\text{PCVS} + 0.0163\text{DUFF})]$	NR	0.869	NA
			$P_m = 1/1 + \exp[-(-3.155 - 0.410\text{DBH} + 0.550\text{PCVS})]$	NR	0.829	NA
	SEGI2	85	$P_m = 1/1 + \exp[-(-166.51 + 1.7296\text{PCVS})]$	NR	0.997	NA
			$P_m = 1/1 + \exp[-(1.7071 - 0.0852\text{DBH})]$	NR	0.836	NA
1K						
McHugh and Kolb (2003)	PIPO	222	$P_m = 1/1 + \exp[-(-13.0829 + 0.1107\text{TCD} + 1.8879\text{CHUPS})]$ (2.1830) (0.0201) (0.5011)	NR	0.94	NA
			$P_m = 1/1 + \exp[-(-6.1425 + 0.0648\text{DBH} + 0.0912\text{TCD})]$ (0.17209) (0.40) (0.0171)	NR	0.92	NA
			$P_m = 1/1 + \exp[-(-9.7149 + 0.0921\text{TCD} + 0.8082\text{CHUPS})]^{\text{F}}$ (0.0070) (0.2029) (0.7649)	NR	0.95	NA
			$P_m = 1/1 + \exp[-(-8.7456 + 0.0128\text{DBH} + 0.0960\text{TCD})]^{\text{F}}$ (0.0070) (0.0050) (0.0070)	NR	0.95	NA

1L						
McHugh *et al.* (2003)	PIPO	222	P_m = 1/1 + exp[− (−8.826 + 0.103TCD + 1.864IAR)] (1.2735) (0.0186) (0.5771)	NR	0.93	NA
1M						
van Mantgem *et al.* (2003)	ABCO	2622	P_m = 1/1 + exp[− (−1.18 − 0.31GR + 0.06PCVS)] (0.33) (0.10) (0.01)	80% (−0.4)	0.96 (calibration) 0.94 (validation)	86% (0.40)
1N						
van Mantgem and Schwartz (2004)	PIPO	53	P_m = 1/1 + exp[− (−4.017 − 0.382CSC + 0.030SSH)] (1.089) (0.190) (0.011)	NR	0.78	NA
1O						
Thies *et al.* (2006)	PIPO	3415	P_m = 1/1 + exp[(−2.2545 − 3.7467LCP + 2.0834NSP + 3.5714BKP (0.5261) (0.8972) (0.3450) (0.5634) + 0.3018BCS + 3.4466BSP)] (0.0505) (0.3196)	91.20%	NA	NA
			P_m = 1/1 + exp[(−4.4635 + 3.3328NSP + 6.6203BSP)] (NR) (0.3153) (0.8879)	89.1% (0.6)	NA	NA
1P						
Schwilk *et al.* (2006)	*Abies* (1 year)	60	P_m = 1/1 + exp[− (−3.1 + 0.41GM)]	NR	NA	NA
	Abies (3 year)	60	P_m = 1/1 + exp[− (−2.1 + 0.23GM)]	NR	NA	NA
	Pinus (1 year)	56	P_m = 1/1 + exp[− (−1.57 − 0.048GM)]	NR	NA	NA
	Pinus (3 year)	55	P_m = 1/1 + exp[− (−0.997 + 0.079GM)	NR	NA	NA
1Q						
Kobziar *et al.* (2006)	ABCO	396	P_m = 1/1 + exp[− (−47.847 − 0.1210DBH + 0.5030TCD + 0.0360DUFF)] (11.697) (0.0400) (0.1180) (0.0140)	98.7 (0.5)	0.998	NA
	CADE27	428	P_m = 1/1 + exp[− (−3.9574 − 0.1892DBH + 0.0540TCD + 1.2266CSRmax)] (1.1049) (0.0416) (0.0086) (0.3593)	90.1 (0.5)	0.95	NA
	LIDE	118	P_m = 1/1 + exp[− (−2.0216 − 0.1144HT + 0.0431TCD)] (1.1436) (0.0627) (0.00992)	88.2 (0.5)	0.947	NA
	PIPO	61	P_m = 1/1 + exp[− (−4.1607 − 0.2542DBH + 0.0922CC)] (2.1657) (0.1129) (0.0452)	91.8 (0.5)	0.958	NA
	PSME	163	P_m = 1/1 + exp[− (−47.847 − 0.1210DBH + 0.5030TCD + 0.0360DUFF)] (11.697) (0.0400) (0.1180) (0.0140)	92.0 (0.5)	0.957	NA
	QUKE	94	P_m = 1/1 + exp[− (−5.6977 + 2.2393CSRopp)] (2.2511) (0.9352)	81.3 (0.5)	0.861	NA
	Site 1	151	P_m = 1/1 + exp[− (1.0535 + 0.0017I − 0.2390HT)] (0.3900) (0.0008) (0.0444)	83.9 (0.5)	0.9144	NA
	Site 2	366	P_m = 1/1 + exp[− (1.5021 + 0.0024I − 0.2505DBH)] (0.4800) (0.0004) (0.0344)	93.4 (0.5)	0.9418	NA
	Site 3	432	P_m = 1/1 + exp[− (1.5381 + 0.0015I − 0.2476DBH + 0.0207CON1000R)] (0.4924) (0.0003) (0.0284) (0.0045)	85.9 (0.5)	0.912	NA
	All	949	P_m = 1/1 + exp[− (1.0337 + 0.00015I − 0.2210DBH + 0.0219CON1000R)] (0.2497) (0.0002) (0.0171) (0.0031)	88.1 (0.5)	0.9223	NA

(*Continued*)

Table A3. (Continued)

Study code Author(s) (year)	Species	Sample size	Model	Accuracy (criteria)	ROC curve value (C)	Validation accuracy (criteria)
1R						
Breece *et al.* (2008)	PIPO	994	$P_m = 1/1 + \exp[-(\underset{(0.510)}{-5.841} + \underset{(0.396)}{3.896}\mathrm{BBAR} + \underset{(0.586)}{3.166}\mathrm{TCD})]$	NR	0.98	NR
			$P_m = 1/1 + \exp[-(\underset{(0.365)}{-3.239} + \underset{(0.450)}{4.832}\mathrm{TCD} - \underset{(0.269)}{0.476}\mathrm{BCS})]$	NR	0.84	NR
			$P_m = 1/1 + \exp[-(\underset{(0.566)}{-4.401} + \underset{(0.488)}{4.422}\mathrm{BBAR} + \underset{(0.789)}{4.748}\mathrm{TCD} - \underset{(0.454)}{1.631}\mathrm{BCS})]$	NR	0.98	NR
1S						
Hood *et al.* (2007*a*)	PICO	151–1550	$P_m = 1/(1 + \exp(-1.941 + 6.316(1 - \exp(-0.3937\ \mathrm{BT})) - 0.000535(\mathrm{CVS}^2))$	NA	0.67–0.79	4–11%
	PIAL	154		NA	0.75	17%
	PIEN	105–266		NA	0.62–0.7	−8–26%
	ABMA	209		NA	0.65	48%
	TSHE	147		NA	0.79	24%
	ABLA	172–905		NA	0.83–0.92	−11–14%
	ABCO	1880		NA	0.79	2%
	CADE27	788		NA	0.88	22%
	PIPO and PIJE	222–7004		NA	0.74–0.93	1–37%
	PSME	118–1482		NA	0.64–0.88	−36–21%
	LAOC	309		NA	0.77	25%
	PILA	109		NA	0.79	−18%
1T						
Conklin and Geils (2008)	PIPO	1585	$P_m = 1/1 + \exp[-(-4.461 + \underset{(0.2182)}{1.6827}\mathrm{CS90} + \underset{(0.2526)}{3.5171}\mathrm{CS100} + \underset{(0.3847)}{0.2779}\mathrm{BCS}^2 + \underset{(0.0437)\ (0.2461)}{0.8455}\mathrm{DMR5} + \underset{(0.1838)}{2.3453}\mathrm{DMR6})]$	NR	NR	NA

[A]Logistic model coefficients in Imperial units.
[B]Ranges in accuracy are for prediction of mortality for different species.
[C]Accuracy was determined by using Cohen's kappa statistic, a chance-corrected classification rate.
[D]Data for model development collected at the tree scale.
[E]Data for model development collected at the plot scale.
[F]Models were developed from both prescribed fire and wildfire data.

Table A4. Wildfire post-fire tree mortality models including tree species modelled, sample size, variable coefficients, modelling procedures, Receiver Operating Characteristics (ROC) curve and accuracy values

Numbers in parentheses below models indicate standard errors of coefficients if reported. NR, not reported in publication

Study code Author(s) (year)	Species	Sample size	Model	Accuracy (criteria)	ROC curve value (C)	Validation accuracy (criteria)
2A						
Peterson and Arbaugh (1986)	PSME	302	$P_s = 1 + \exp(-6.944 + 0.063CS + 1.004ID)$	NA	NA	NA
	PICO	243	$P_s = 1 + \exp(-3.874 + 0.039CS + 0.023BS)$	NA	NA	NA
2B						
Peterson and Arbaugh (1989)	PSME	294	$P_s = 1 + \exp[-(-2.79 + 1.43SITE1 + 1.58LC1 + 0.38CS + 4.04BCR - 0.63BT)]$	NR	NA	NA
			$P_s = 1 + \exp[-(-2.79 + 1.43SITE1 - 0.49LC2 + 0.38CS + 4.04BCR - 0.63BT)]$	NR	NA	NA
			$P_s = 1 + \exp[-(-2.79 + 1.43SITE1 - 0.92LC3 + 0.38CS + 4.04BCR - 0.63BT)]$	NR	NA	NA
			$P_s = 1 + \exp[-(-2.79 + 1.43SITE1 - 0.80LC4 + 0.38CS + 4.04BCR - 0.63BT)]$	NR	NA	NA
			$P_s = 1 + \exp[-(-2.79 - 0.82SITE2 + 1.58LC1 + 0.38CS + 4.04BCR - 0.63BT)]$	NR	NA	NA
			$P_s = 1 + \exp[-(-2.79 - 0.82SITE2 - 0.49LC2 + 0.38CS + 4.04BCR - 0.63BT)]$	NR	NA	NA
			$P_s = 1 + \exp[-(-2.79 - 0.82SITE2 - 0.92LC3 + 0.38CS + 4.04BCR - 0.63BT)]$	NR	NA	NA
			$P_s = 1 + \exp[-(-2.79 - 0.82SITE2 - 0.80LC4 + 0.38CS + 4.04BCR - 0.63BT)]$	NR	NA	NA
			$P_s = 1 + \exp[-(-2.79 - 1.22SITE3 + 1.58LC1 + 0.38CS + 4.04BCR - 0.63BT)]$	NR	NA	NA
			$P_s = 1 + \exp[-(-2.79 - 1.22SITE3 - 0.49LC2 + 0.38CS + 4.04BCR - 0.63BT)]$	NR	NA	NA
			$P_s = 1 + \exp[-(-2.79 - 1.22SITE3 - 0.92LC3 + 0.38CS + 4.04BCR - 0.63BT)]$	NR	NA	NA
			$P_s = 1 + \exp[-(-2.79 - 1.22SITE3 - 0.80LC4 + 0.38CS + 4.04BCR - 0.63BT)]$	NR	NA	NA
2C						
Regelbrugge and Conard (1993)	PIPO	825	$P_m = 1/1 + \exp[-(1.0205 - 0.0933DBH + 0.2858CH)]$	NR	0.93	90%
			$P_m = 1/1 + \exp[-(-2.2697 + 7.5662RCH)]$	NR	0.914	81% (−0.5)
	CADE27	51	$P_m = 1/1 + \exp[-(-0.1148 - 0.0713DBH + 0.2642CH)]$	NR	0.844	NA
			$P_m = 1/1 + \exp[-(-2.3205 + 4.0242RCH)]$	NR	0.83	NA
	QUKE and QUCH	125	$P_{tk} = 1/1 + \exp[-(2.1327 - 0.01676DBH + 0.2858CH)]$	NR	0.968	NA
			$P_{tk} = 1/1 + \exp[-(-2.3240 + 20.2875RCH)]$	NR	0.961	NA
2D						
Borchert *et al.* (2002)	PICO3 and PISA2	263	$P_s = 1 + \exp[-(3.6791 - 0.0455PCS - 0.2301HBC + 1.1436SPECIES)]$	83% (−0.5)	NA	NA
	PICO3	146	$P_s = 1 + \exp[-(5.889 - 0.0773PCS - 0.4203HBC)]$	NR	NA	NA
	PISA2	117	$P_s = 1 + \exp[-(4.3850 - 0.0409PCS - 0.2079HBC)]$	NR	NA	NA

(*Continued*)

Table A4. (Continued)

Study code Author(s) (year)	Species	Sample size	Model	Accuracy (criteria)	ROC curve value (C)	Validation accuracy (criteria)
2E						
McHugh and Kolb (2003)	PIPO	1145	$P_m = 1/1 + \exp[-(-13.6452 + 1.268\text{TCD} + 0.9914\text{CHUPS})]$ (1.8584) (0.0179) (0.3115)	NR	0.93	NA
			$P_m = 1/1 + \exp[-(-9.9728 + 0.0852\text{TCD} + 1.3421\text{CHUPS})]$ (1.7900) (0.0084) (0.7507)	NR	0.96	NA
			$P_m = 1/1 + \exp[-(-14.8856 + 0.0348\text{DBH} + 0.1554\text{TCD})]$ (2.1338) (0.0106) (0.0216)	NR	0.93	NA
			$P_m = 1/1 + \exp[-(-8.2851 + 0.0169\text{DBH} + 0.0875\text{TCD})]$ (0.9354) (0.0087) (0.0086)	NR	0.96	NA
2F						
McHugh *et al.* (2003)	PIPO	312 (spring)	$P_m = 1/1 + \exp[-(-11.682 + 0.116\text{TCD} + 2.047\text{IAR})]$ (1.7693) (0.0194) (0.3093)	NR	0.96	NA
		833 (summer)	$P_m = 1/1 + \exp[-(-7.979 + 0.087\text{TCD} + 1.321\text{IAR})]$ (0.8073) (0.0091) (0.2820)	NR	0.97	NA
2G						
Raymond and Peterson (2005)	PSME	244	$P_m = 1/1 + \exp[-(-2.576 + 0.050\text{CS})]$	87% (0.6)	NA	NA
			$P_m = 1/1 + \exp[-(0.277 - 0.082\text{DBH} + 0.053\text{CS})]$	90% (0.6)	NA	NA
			$P_m = 1/1 + \exp[-(-3.977 - 0.055\text{CS} + 1.323\text{NDEAD})]$	91% (0.6)	NA	NA
			$P_m = 1/1 + \exp[-(-1.540 - 0.079\text{DBH} + 0.062\text{CS} + 1.348\text{NDEAD})]$	93% (0.6)	NA	NA
			$P_m = 1/1 + \exp[-(-0.331 - 0.115\text{DBH} + 0.055\text{CS} + 1.336\text{NDEAD} + 3.539\text{TRT})]$	NR	NA	NA
2H						
Sieg *et al.* (2006)	PIPO	1257 (AZ)	$P_m = 1/1 + \exp[-(-1.32985 + 0.00069\text{CSV2} + 0.00001\text{CSV3} + 0.04687\text{CCV} - 2.19528\log\text{DBH} + 0.4214\sqrt{\text{BSL}} - 2.04983\text{DEN} + 1.591\sqrt{\text{GSV}})]$	91.0% (0.5)	0.96	NA
		947 (CO)	$P_m = 1/1 + \exp[-(-4.2779 + 0.084956\text{CSV} - 0.0019\text{CSV2} + 0.0000156\text{CSV3} + 0.06676\text{CCV} - 2.0244\log\text{DBH} - 2.567\text{IPS})]$	84.8% (0.5)	0.94	NA
		1244 (SD)	$P_m = 1/1 + \exp[-(-1.46072 + 0.072461\text{CCV} + 0.000004541\text{CSV3} - 2.93438\text{IPS} + 3.533568\sqrt{\text{GSV}} + 0.48483\sqrt{\text{BSL}} - 2.41467\log\text{DBH} - 0.016\text{BSC})]$	91.5% (0.5)	0.97	NA
		1635 (MT)	$P_m = 1/1 + \exp[-(1.184817 + 0.10403\text{CCV} + 0.000005404\text{CSV3} - 3.0373\text{IPS} - 1.76628\log\text{DBH} - 0.03897\text{BSC} - 0.0002625\text{LCR})]$	92.5% (0.5)	0.97	NA
		5083 (ALL)	$P_m = 1/1 + \exp[-(0.0734 - 2.4678\log\text{DBH} + 0.0942\text{CSV} - 0.0024\text{CSV2} + 0.000019\text{CSV3} + 0.05214\text{CCV} - 0.0002\text{LCR} + 0.1588\log\text{BSH} + 0.3.698\sqrt{\text{BSL}} + 1.4257\sqrt{\text{GSV}} + 2.4978\text{IPS})]$	89.9% (0.5)	0.96	95.70%
			$P_m = 1/1 + \exp[-(-0.12 - 1.6238\log\text{DBH} + 0.07\text{CCV} + 0.1084\text{CSV} - 0.0025\text{CSV2} + 0.00002\text{CSV3} - 2.9235\text{IPS})]$	89.3% (0.5)	0.96	NA
			$P_m = 1/1 + \exp[-(-2.6513 + 0.1132\text{lCSV} - 0.0029\text{CSV2} + 0.00002\text{CSV3} - 0.0808\text{CCV})]$	84.8% (0.5)	0.92	NA
2I						
Keyser *et al.* (2006)	PIPO	722	$P_m = 1/1 + \exp[-(-0.237 - 0.098\text{DBH} + 0.027\text{PSCOR} + 0.022\text{CHAR})]$	NR	0.83	78% (0.5)
		721	$P_m = 1/1 + \exp[-(0.538 - 2.038\text{BARK} + 0.021\text{PSCOR} + 0.019\text{CHAR})]$	NR	0.86	79%

2J						
Hood *et al.* (2007*d*)	ABCO					
	(2 years post fire)	1866	$P_m = 1/1 + \exp[-(-4.2913 + 0.000006\text{PCLK}^3 + 0.2185\text{CKR} + 0.0174\text{DBH})]$	NR	0.87	NA
	(3 years post fire)	424	$P_m = 1/1 + \exp[-(-5.3456 + 0.000006\text{PCLK}^3 + 0.6584\text{CKR} + 0.0367\text{DBH} + 0.5308\text{AB})]$	NR	0.91	NA
	CADE27	781	$P_m = 1/1 + \exp[-(-4.9369 + 0.0000068\text{PCLK}^3 + 0.5398\text{CKR} - 0.0143\text{DBH})]$	NR	0.92	NA
	PIPO and PIJE					
	(pre-bud break)	1974	$P_m = 1/1 + \exp[-(-6.8243 + 0.000568\text{PCLS}^2 + 0.6688\text{CKR} + 0.0285\text{DBH})]$	NR	0.87	NA
	(post-bud break)		$P_m = 1/1 + \exp[-(-4.3202 + 0.0000723\text{PCLK}^2 + 0.4185\text{CKR} + 0.0188\text{DBH} + 0.9048\text{RTB})]$	NR	0.92	NA
	ABMA	206	$P_m = 1/1 + \exp[-(-4.2066 + 0.0330\text{PCLK} + 0.8702\text{CKR} + 0.4619\text{AB})]$	NR	0.83	NA
2K						
Hood and Bentz (2007)	PSME	789	$P_m = 1/1 + \exp[-(-0.8435 + 0.03719\text{PCVS} + 0.4786\text{CKR} - 0.03015\text{DBH} - 2.2999\text{DFB}$ (0.5262) (0.004771) (0.09393) (0.01102) (0.7746) $+ 0.09395 + \text{DBH} \times \text{DFB})]$ (0.01815)	77.40% (0.5)	0.90[A] 0.94[A]	83%[A] (0.6)
2L						
Hanson and North (2009)	PIPO and PIJE	142	$P_s = 1/1 + \exp[-(23.082 - 0.166\text{CKC} - 2.239\text{BC} - 0.061\text{CCC})]$ (0.5035) (0.044) (0.773) (0.023)	88% (NR)	NA	NA
	ABMA	57	$P_s = 1/1 + \exp[-(2.744 - 2.869\text{BC} + 0.056\text{DBH})]$ (1.648) (0.779) (0.018)	83% (NR)	NA	NA
2M						
Hood *et al.* (2010)	ABCO	2175	$P_m = 1/1 + \exp[-(-2.9075 + 0.000006227\text{CLK}^3 + 0.0159\text{DBH} + 0.2761\text{CKR} + 0.5664\text{AB})]$ (0.2591) (0.000000273) (0.0028) (0.0467) (0.1114)	82/74%[B] (0.5)	0.87	NA
	CADE27	783	$P_m = 1/1 + \exp[-(-5.2153 + 0.000006942\text{CLK}^3 + 0.4836\text{CKR})]$ (0.4365) (0.0000005823) (0.1165)	70/92% (0.5)	0.92	NA
			$P_m = 1/1 + \exp[-(-5.5477 + 0.000006196\text{CVK}^3 + 0.4543\text{CKR})]$ (0.4645) (0.0000005262) (0.1159)	73/93% (0.5)	0.92	NA
	PILA	714	$P_m = 1/1 + \exp[-(-0.9257 + 0.000009387\text{CLK}^3 - 1.0963\text{CKR} + 0.9214\text{RTB})]$ (0.1700) (0.0000009781) (0.1420) (0.1211)	87/85% (0.5)	0.93	NA
	PIJE and PIPO	2005	$P_m = 1/1 + \exp[-(-4.7732 + 0.0011\text{CLK}^2 + 0.0011\text{CKR} + 1.0334\text{RTB})]$ (0.4155) (0.000101) (0.1131) (0.1415)	92/89% (0.5)	0.97	NA
			$P_m = 1/1 + \exp[-(-7.5516 + 0.000687\text{CLS}^2 + 1.0205\text{CKR} + 1.1146\text{RTB})]$ (0.6994) (0.0000717) (0.1060) (0.1336)	90/91% (0.5)	0.96	NA
			$P_m = 1/1 + \exp[-(-5.4174 + 0.000966\text{CVK}^2 + 0.8610\text{CKR} + 1.0483\text{RTB})]$ (0.4770) (0.0.0000928) (0.1140) (0.1453)	92/90% (0.5)	0.97	NA
			$P_m = 1/1 + \exp[-(-10.1328 + 0.000946\text{CVS}^2 + 0.9971\text{CKR} + 1.1451\text{RTB})]$ (1.0258) (0.0.000106) (0.1051) (0.1347)	90/90% (0.5)	0.96	NA

[A]ROC curve value is for a validation dataset of 547 Douglas-fir from prescribed burns on the Lubrecht Experimental Forest, MT.
[B]Percentage true positive/percentage true negative.

Table A5. Model parameter codes and definitions for prescribed and wildfire studies predicting tree mortality
Species codes follow guidelines of the USDA plants database (http://plants.usda.gov/java/, accessed 16 August 2011)

Study code(s)	Variable code	Definition
1B–1T, 2C–2M	P_m	Probability of mortality
1A, 2A, 2B, 2D	P_s	Probability of survival
1G, 2C	P_{tk}	Probability of top killing
All	D	Diameter at breast height (centimetres or inches)
	DBH	
1H	D	Diameter class (7.5, 15.0, 22.5 or 30.0 cm)
1M	GR	Average annual radial growth rate
2D	SPECIES	Tree species
1B, 1S, 2B	BT	Bark thickness (centimetres or inches)
2I	BARK	
1O	LCP	Live crown proportion
2H	LCR	Live crown ratio
1Q	CC	Canopy cover
1Q	HT	Tree height
Crown damage variables		
1A, 1F, 1G	SH	Crown scorch height (metres or feet)
1I, 1J,	PCVS	Percentage crown volume scorched
1M, 1S	C	
2A, 2B, 2G	CS	
2H, 2K, 2M	CSV	
	CVS	
1N	CSC	Percentage crown volume scorched class (0–5, 6–20, 21–50, 51–80, 81–95, 95–100)
1T	CS90	Crown scorch length class of 90%
	CS100	Crown scorch length class of 100%
1E	CS	Percentage of live crown length scorched
2I	PSCOR	
2J	PCLK	Percentage of pre-fire crown length killed
2J	PCLS	Percentage crown length scorched
1O	NSP	Needle scorch proportion
1O	BKP	Bud kill proportion
2D	PCS	Percentage crown scorch length
1G	FCVS	Fraction crown volume scorched
1J	SCHT	Crown scorch height
1H	L	Low crown scorch length (50%, 1; 90%, 0; 100, −1)
	H	High crown scorch length (50%, 0; 90%, 1; 100, −1)
2M	CLK	Crown length killed
1B	CK	Percentage crown volume killed
2M	CVK	
2L	CKC	Crown volume killed class (e.g. 60–69.9, 70–79.9, 80–89.9, 90–99.9)
2H	CCV	Percentage crown volume consumed
2L	CCC	% crown consumption class (0–19, 20–39, 40–59, 60–79, 80–100)
1K, 1L, 1Q, 1R, 2E	TCD	Total crown damage (percentage crown volume scorched + percentage crown volume consumed)
Bole damage variables		
2A	BS	Bole scorch (percentage basal circumference charred at 0.5 m)
2C	RCH	Relative char height (height of stem bark char as a proportion of tree height)
1N	SSH	Stem scorch height
2D	HBC	Height of bark char (m)
1C	TL	Calculated duration of lethal heat (minutes)
1C	TC	Calculated critical time for cambial kill (minutes)
2J, 2M	CKR	Cambium kill rating (*n* of dead cambium quadrants; 1–4)
2B	LC	Live cambium
1D, 1H	N, NDEAD	Number of dead cambium samples
2G		
1K,2E	CHUPS	Bole char severity rating – leeward side (0 = none, 1 = light char, 2 = medium char, 3 = heavy char)
1R, 1T	BCS	
2L	BC	Composite of amount and severity of bole char (1 = low, 2 = medium, 3 = high)
2H	BSL	Minimum bole scorch height

2A	BCR	Bark char ratio (ratio of mean bark char depth to mean bark thickness)
2I	CHAR	Percentage of bole circumference charred
2C	CH	Height of stem bark char (m)
1O	BSP	Bole scorch proportion (maximum bole scorch height as a proportion of total tree height)
1O	BSC	Basal char severity (*n* of quadrants with basal char class 3 or 4))
2H	BSC	Basal circumference scorch (percentage scorched at 30 cm above the ground)
1Q	CSR_{max}	Bole char severity rating at the highest bole scorch position
	CSR_{opp}	Opposite maximum bole char below 30.5 cm (1 = bark black but not consumed, 2 = entire bark and fissures blackened but not consumed, 3 = entire bark and fissures blackened with significant consumption)
1P	GM	Geometric mean of average plot crown scorch height and average plot bole char height surrogate of fire intensity
Ground severity variables		
1G	FC	Fuel consumption (duff, litter, 1-, 10-, 100-h fuels)
1G	UDWC	Uphill duff and litter weight consumption
1G	UDDC	Uphill duff and litter depth consumption (cm)
1J, 1Q	DUFF	Forest floor consumption (cm)
1Q	CON1000R	Consumption of 1000-h time-lag fuels
2H	GSV	Ground fire severity (0–4)
Insect and pathogen variables		
2H	IPS	Presence of *Ips*
2H	DEN	Presence of *Dendroctonus*
2A	ID	Insect damage (low, medium, high)
2J, 2M	AB	Ambrosia beetle (*Gnathotricus*, *Treptoplatypus, Trypodendron*, *Xyleborus*), percentage bole circumference attacked
2J, 2M	RTB	Red turpentine beetle (*Dendroctonus valens*), *n* of pitch tubes on bole
2K	DFB	Douglas-fir beetle (*Dendroctonus pseudotsugae*), percentage bole circumference attacked
1L	IAR	Insect attack rating or bark beetle attack rating (*Ips* and *Dendroctonus*)
1S	BBAR	(0, no evidence bark beetle activity; 1, bark beetle activity <75% but >0% of bole circumference; 2, >75% of bole circumference)
1E,1T	DMR	Dwarf mistletoe rating (1–6)
Fire severity and intensity variables		
1Q	I	Fireline intensity (kW m^{-1})
1G	FL	Flame length
1H	S	Season (dormant and growing)
2G	TRT	Fuel treatment (thinned, thinned + underburned, thinned + coarse woody debris, control)
Species codes	Scientific name	Common name
ABCO	*Abies concolor*	White fir
ABGR	*Abies grandis*	Grand fir
ABLA	*Abies lasiocarpa*	Subalpine fir
ABMA	*Abies magnifica*	Red fir
CADE27	*Calocedrus deccurrens*	Incense-cedar
LAOC	*Larix occidentalis*	Western larch
LIDE3	*Lithocarpus densiflorus*	Tanoak
PIAL	*Pinus albicaulis*	Whitebark pine
PICO	*Pinus contorta*	Lodgepole pine
PICO3	*Pinus coulteri*	Coulter pine
PIEN	*Picea engelmannii*	Engelmann spruce
PIJE	*Pinus jeffreyii*	Jeffrey pine
PILA	*Pinus lambertiana*	Sugar pine
PIPO	*Pinus ponderosa*	Ponderosa pine
PISA2	*Pinus sabiniana*	California foothill pine
PSME	*Pseudotsuga mensiezii*	Douglas-fir
QUKE	*Quercus keloggii*	Oregon white oak
QUCH2	*Quercis chrysolepis*	Canyon live oak
SESE3	*Sequoia sempervirens*	Coast redwood
SEGI2	*Sequoiadendron giganteum*	Giant sequoia
THPL	*Thuja plicata*	Western red cedar
TSHE	*Tsuga heterophylla*	Western hemlock