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Prediction of delayed mortality of fire-damaged ponderosa pine following prescribed fires in eastern Oregon, USA

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Abstract. Prescribed burning is a management tool used to reduce fuel loads in western interior forests. Following a burn, managers need the ability to predict the mortality of individual trees based on easily observed characteristics. A study was established in six stands of mixed-age ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.) with scattered western junipers at the south end of the Blue Mountains near Burns, Oregon, USA. Stands were thinned in either 1994 or 1995. Three treatments, a fall burn, a spring burn, and an unburned control, were randomly assigned to 12-ha experimental units within each stand. Prescribed burns occurred during mid-October of 1997 or mid-June of 1998 and were representative of operational burns, given weather and fuel conditions. Within each experimental unit, six 0.2-ha plots were established to evaluate responses to the burns. Ponderosa pine plot trees ($n = 3415$) alive 1 month after the burns were evaluated and observed for four growing seasons. Nine fire damage and tree morphological variables were evaluated by logistic regression. A five-factor full model and a two-factor reduced model are presented for projecting probability of mortality. Significant variables in the full model included measures of crown, bole, and basal damage.

Additional keywords: Blue Mountains; modeling.

Introduction

Prescribed burning is currently being used as a management tool to reduce fuel loads and to restore ecosystem function in western interior forests of the USA. Following a prescribed fire, one measure of the fire is the immediate and predicted delayed mortality of trees in the treated unit. Managers evaluate this mortality in order to determine the success of burning prescriptions to achieve such management objectives as post-fire stocking levels, to improve future prescriptions, and to better plan additional activities (e.g. planting). Post-fire predictions need to be based on easily observable morphological and burn-damage characteristics.

Significant effort has gone into developing tools to predict mortality of fire-damaged ponderosa pine. Comprehensive literature reviews of fire-caused mortality (McHugh 2001) and of methods to predict mortality (Fowler and Sieg 2004) of ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.) in western USA are available. Discriminant analysis and logistic regression have been used to select variables and develop models that predict fire-induced ponderosa pine mortality based on easily observable tree damage. Three studies report discriminant analysis models predicting fire-caused mortality of ponderosa pine from prescribed fire (Wyant and Zimmerman 1983; Wyant *et al*. 1986; Swezy and Agee 1991). Logistic regression models specifically for predicting ponderosa pine mortality following fire are reported from seven studies: four with data from prescribed fire (Harrington and Hawksworth 1990; Saveland *et al*. 1990; Harrington 1993; Stephens and Finney 2002), two with data from wildfires (Regelbrugge and Conard 1993; Finney 1999), and one with data from a combination of wildfire and prescribed fire (McHugh and Kolb 2003). Ryan and Reinhardt (1988) used data from 43 prescribed fires and seven western conifer species (not including ponderosa pine) to develop a logistic regression model that may have broad application geographically and in mixed-conifer stands. There is general agreement that tree size, bole scorch, and crown damage are useful descriptors to predict delayed post-fire mortality of trees. Although the effect of season of prescribed burn has received ample speculation, few studies have focused on this. Harrington (1987, 1993)

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Table 1. Pre- and post-burn means of stand and tree size characteristics
Data collected fall 1998. dbh, diameter at breast height; NA, not applicable

Treatment	dbh (cm)		Tree height (m)		Trees per ha		Basal area (m^2/ha)		Experimental unit		
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Area (ha)	Burned (%)	Slope (%)
Control	28.4	28.5	14.0	14.0	226	224	17.9	17.8	9.4	NA	14
Fall	26.3	28.8	13.8	14.5	264	179	18.8	14.4	15.1	56	18
Spring	27.4	28.3	13.9	14.2	246	218	18.4	17.6	15.1	57	14

specifically tested the impact of season of burn on ponderosa pine mortality in a replicated experiment in Colorado. He reported higher mortality with spring (active season) burns than with fall (dormant season) burns. In contrast, Thies *et al*. (2005) examined the effect of season of prescribed burn on ponderosa pine mortality in Oregon and reported higher mortality with fall burns than with spring burns.

The present paper reports on the development of logistic regression models to predict delayed mortality of individual ponderosa pines based on post-fire observations. Data were collected from six ponderosa pine stands in eastern Oregon that were observed for four growing seasons following prescribed burning. To observe the full range of operational burns in these stands, study treatments included spring and fall burns and an unburned control. The explanatory variables represented tree morphology, fire damage, and season of burn.

Methods and materials

Experimental design and sampling

The study was established in six stands of mixed-age ponderosa pine with scattered western junipers (*Juniperus occidentalis* Hook.) and mountain-mahogany (*Cercocarpus ledifolius* Nutt.) at the south end of the Blue Mountains (Emigrant Creek Ranger District, Malheur National Forest) near Burns, Oregon, USA. Each stand was thinned from below in either 1994 or 1995, and burns were prescribed to reduce untreated thinning slash, reduce over-stocking of saplings in some areas, stimulate low levels of natural regeneration where little existed, create snags, reinvigorate shrubs and herbaceous plants, and reintroduce fire into ecosystems with a history of frequent fire. Additional details are available regarding site, stand structure, and the burn treatments (Thies *et al*. 2005) and understory vegetation (Kerns *et al*. 2006).

Each stand was designated as a replicate and divided into three contiguous experimental units similar in type, aspect, and slope. Three treatments, no-burn, fall burn, and spring burn, were randomly assigned to experimental units within each replicate. Experimental units were burned during mid-October of 1997 (fall burn) or mid-June of 1998 (spring burn). Thus, at each examination, all 18 experimental units had developed without further disturbance for the same number of growing seasons. All burns were carried out within the burn prescription and were representative of operational burns, given weather and fuel conditions.

Because of the uncertain availability of appropriate conditions for prescribed burns, plot establishment and data collection were not begun until after the burns were completed. Within each experimental unit, six 0.2-ha circular sampling plots were established post fire, at least 100 m apart and in locations representative of the average stand and burn conditions in the experimental unit. Areas having few ponderosa pines, such as a rock outcropping or a thicket of mountain-mahogany, were avoided. On each plot, all standing conifers (excepting junipers) greater than 7.5 cm diameter at breast height (dbh) were tagged. Some stand and experimental unit characteristics are summarized in Table 1; additional detail can be found in Thies *et al*. (2005).

Each tree alive at the time of the burns was classified in July 1998 (1 month after the spring burn) as either alive (if the tree had some green needles) or dead (if all needles were either consumed or scorched). Scorched needles are those discolored owing to heat from the fire. Trees dead pre-burn were recognized by bark condition, presence of decay, and lack of needles and fine twigs. Trees killed outright by the fire were called immediate mortality. Trees that died (likely as a result of the fire) after July 1998 were called delayed mortality. Experimental units were evaluated for delayed mortality in the falls of 1998, 1999, 2000, and 2001. By fall 2001, annual mortality on burned and unburned units was similar (Thies *et al*. 2005). Only those trees alive in July 1998 were evaluated for burn damage and used to develop models for probability of delayed mortality for individual trees.

Data collection

Data were collected on tree crowns, stems, and tree quadrants in fall 1998. The variables, measures of tree morphology, and fire damage are from data collected in fall 1998 and are shown in italics throughout the text. Variables analyzed in the present paper are listed in Table 2. Three criteria governed variable selection: (1) each variable provided a measure of fire damage or tree quality known or expected to influence post-fire mortality; (2) each variable was quickly and precisely measurable with non-destructive sampling procedures; and (3) variables measured were readily observable soon after fire.

Table 2. Variables analyzed with their means and standard errors (s.e.) for trees in the prescribed burn areas classed as survivors or as delayed mortality through fall 2001

Variable	Surviving trees ($n = 2865$) Mean	s.e.	Delayed mortality ($n = 550$) Mean	s.e
Morphological variables				
Diameter at breast height (cm)	28.61	0.28	22.98	0.49
Tree height (m)	14.40	0.12	13.01	0.22
Live crown proportion	0.58	0.01	0.54	0.01
Damage variables				
Needle scorch proportion	0.18	0.01	0.73	0.02
Bud kill proportion	0.06	0.01	0.54	0.02
Ground char severe (0–4)	1.72	0.03	2.81	0.07
Basal char severe (0–4)	0.52	0.02	1.39	0.06
Basal char minimum (0–4)	1.11	0.01	1.76	0.03
Bole scorch proportion	0.11	0.01	0.30	0.01

Tree diameters

Diameter at breast height (*dbh*) is the tree diameter measured to the nearest 0.25 cm on the uphill side of the tree at 1.37 m above mineral soil.

Crowns

Each crown, post fire, may exhibit some or all of the following three layers depending on the amount of heat damage, from top to bottom: green (alive, undamaged); scorched needles but buds alive; and killed needles and buds. Immediately post fire, crowns that are alive but damaged show two layers: an upper green layer and a lower brown layer of scorched or consumed needles. By the end of the first growing season post fire, the scorched zone may differentiate into two zones: an upper layer where needles but not buds were killed and the buds flushed and green needles started to grow (regreen), and a lower layer that remained brown where both needles and buds were killed. Damage layers often were asymmetrical. Their height was taken as the average height for that layer measured at the bole. Heights were measured to the nearest 3.0 cm with a laser range finder with inclinometer, in descending order:

- *Tree height* – height measured to the tip, trees with broken or damaged tops were not measured;
- *Live crown base post fire* – lower limit of green crown immediately post fire (also defined as the upper limit of needle scorch);
- *Live crown regreen* – lower limit of live crown as seen at the end of the first growing season; and
- *Crown base pre-fire* – lower height of live crown (whorl of three or more live branches) as it existed pre-fire.

Three crown variables are proportions of the crown and are derived from the four measurements given above. *Live crown proportion* is the crown length pre-fire as a proportion of the tree height, a common measure of tree vigor. *Needle scorch proportion* is the proportion of damaged crown length based on scorched needles. This measure of crown damage has been used by others (Herman 1954; Wyant and Zimmerman 1983; Wyant *et al*. 1986; Harrington 1987, 1993; Harrington and Hawksworth 1990) and allowed reproducible results with a minimum of training of field crews. *Bud kill proportion* is the proportion of crown length wherein the temperature was high enough to kill all buds on the branches. Needles do not reappear (regreen) on these branches and the branches are considered dead. The crown variables were calculated from the following equations:

$$\begin{aligned} \textit{Live crown proportion} &= (\textit{tree height} - \textit{crown base pre-fire})/\textit{tree height}, \\ \textit{Needle scorch proportion} &= (\textit{crown base post fire} - \textit{crown base pre-fire})/(\textit{tree height} - \textit{crown base pre-fire}), \\ \textit{Bud kill proportion} &= (\textit{live crown regreen} - \textit{crown base pre-fire})/(\textit{tree height} - \textit{crown base pre-fire}). \end{aligned}$$

Quadrant

External indicators of fire-caused tree damage were recorded as a non-destructive surrogate measure of damage to the cambium, conducting tissues, or roots. The cambium was not sampled or exposed. Data were collected for each quadrant of a tree. Because the uphill side of a tree often gets hotter, quadrants were established and defined in relation to the ground slope: uphill, downhill, right or left (as viewed from the downhill side) of the tree. Because char and consumption of bark and duff during fire is often asymmetrical, each quadrant was evaluated, the values recorded and, in some cases, aggregated to provide a value for the tree:

- *Ground char* – most complete consumption of the litter and duff observed in that quadrant as seen 15 cm from the tree (burn classes modified from Ryan 1983): 0 = unburned, no visible effect to the organic layer; 1 = light, litter and duff layers are scorched or charred but duff is not significantly altered; 2 = moderate, litter is completely consumed and the duff is deeply charred; 3 = consumed, duff is completely consumed, ash only can be seen but the mineral soil surface is not altered; and 4 = deep, litter and duff are completely consumed and the structure and color of the mineral soil surface are visibly altered;
- *Basal char* – most severe char class observed at the duff-line in the quadrant (modified from Ryan 1983): 0 = none, no evidence of flame having contacted the bole and no charring or darkening of bole; 1 = superficial, evidence of light scorching that occurs around the fringe of

more deeply charred bark; 2 = moderate, bark is uniformly black with the possible exception of the inner depths of prominent fissures, but bark character is still discernible; 3 = deep, bark is deeply charred, but not necessarily to the wood, surface characteristics of the bark have been lost; and 4 = wood, bark is burned off with wood clearly showing;
- *Bole scorch* (height) – distance from mineral soil to the highest point of bole blackening, measured to the nearest 15 cm with a height pole.

Derived variables were used to systematically establish tree-level values for variables rated by quadrants:

- *Ground char severe* – number of quadrants with ground char class of 3 or 4 (range 0–4); a ground char class of 3 or 4 was anticipated to generate adequate heat to kill surface roots, and thus was a surrogate value for the proportion of the tree circumference with the potential for killed surface roots;
- *Basal char severe* – number of quadrants with basal char class 3 or 4; we anticipated that heat adequate to cause char of class 3 or 4 would kill the cambium, so this is a surrogate for the proportion of the tree circumference with killed cambium (range 0–4);
- *Basal char minimum* – the minimum char rating on any quadrant on the tree; this variable will test if one quadrant with little char predicts survival;
- *Bole scorch maximum* – the maximum bole scorch height found on any of the four quadrants;
- *Bole scorch proportion* – maximum bole scorch height as a proportion of total tree height (same as relative scorch height in Regelbrugge and Conard 1993), calculated with the formula *bole scorch proportion = bole scorch maximum/tree height*.

To characterize litter and duff, the depth of the organic material to mineral soil was measured on each of the six unburned experimental units. The depth at each tree was taken in the center of each quadrant, 15 cm from the tree base. An additional 28 random points were measured at each experimental unit.

Data analysis

Tree mortality represents a binary categorical response variable. Trees alive in 1998 before the treatment burns were applied were coded as alive (0) or dead (1) in 2001. Logistic regression analysis was used to investigate how this categorical response variable (mortality through 2001) was associated with a set of explanatory variables. Logistic regression is the appropriate statistical technique to model the probability of an event such as a tree dying (McCullagh and Nelder 1991; Ramsey and Schafer 1997; Hosmer and Lemeshow 2000). Monserud (1976) contrasts this modeling form to other prediction functions and recommends its use for analysis of binary data. Several studies have used logistic regression to model the effects of fire on ponderosa pine mortality (Harrington and Hawksworth 1990; Saveland *et al.* 1990; Harrington 1993; Regelbrugge and Conard 1993; Finney 1999; Stephens and Finney 2002; McHugh and Kolb 2003). Other studies (Hamilton 1974, 1990; Ryan and Reinhardt 1988; Vanclay 1991; Avila and Burkhart 1992; van Mantgem *et al.* 2003) have successfully used logistic regression to model mortality of other tree species.

The response (dependent) variable in logistic regression of binary data is the logit, the natural logarithm of the odds ratio $p/(1-p)$, where p is the probability of a variable value being in one of the two categories, alive or dead. The logit transformation converts the probability of mortality into a continuous variable that is linear with respect to the explanatory (independent) variables (McCullagh and Nelder 1991). The logistic regression model is then represented as:

$$\text{logit}(p) = \beta_0 + \beta_1 X_1 + \cdots + \beta_i X_i + Error,$$

where p equals the probability of tree mortality during the period of observation, β_0 is the intercept, β_1 is the regression coefficient for the first explanatory variable (X_1) and β_i is the regression coefficient for the ith explanatory variable (X_i).

Two of the independent variables, *season of burn* and *basal char minimum*, are categorical variables. These variables were analyzed as a series of indicator variables to correctly evaluate their importance in the model. An indicator variable indicates group membership and is equal to 1 for an observation that belongs to one particular category or is equal to 0 for an observation that does not belong to that category. For every k categories of an independent variable, $k-1$ indicator variables must be constructed. *Season of burn* has two categories, spring and fall, and needed only one indicator variable. *Basal char minimum* can take on one of the five categories of basal char. In our data, values for basal char were observed for only four of the five possible categories, therefore only three indicator variables were necessary for our analysis of this independent variable.

Coefficients for logistic regression are usually estimated by using the method of maximum likelihood, which optimizes the probability that the values predicted by the set of model coefficients match the observed data (McCullagh and Nelder 1991). To analyze clustered data where there are potential correlations within clusters, generalized estimating equation (GEE) procedures are used (Liang and Zeger 1986; Zeger and Liang 1986; Hardin and Hilbe 2003). The GEE method was developed for analysis of clustered data for which generalized linear models (GLM) are appropriate, that is, dependent, non-normal data. GEE is an extension to the standard array of GLM analytical techniques that incorporate a correlation structure into the analysis (Liang and Zeger 1986; Zeger and Liang 1986). The correlation structure is specified in the form of a working correlation matrix.

The GEE method estimates model parameters by iteratively solving a system of equations based on quasi-likelihood distributional assumptions through a specific link function and a variance that is a function of the mean (Hardin and Hilbe 2003). For binary data, the binomial distribution is applied through the logit link function. The variance of a binomially distributed population with mean μ is equal to $\mu/(1-\mu)$.

Because of the potential for responses to be similar within experimental units, we used the GEE method for our logistic regression analyses, employing the exchangeable correlation structure. An iterative approach using residuals was used to estimate the correlation between individual trees (Liang and Zeger 1986). Iteration was continued until convergence was reached. Exchangeable correlation structure assumes that the correlation between any two responses in an experimental unit is the same (Hardin and Hilbe 2003). The GEE method yields consistent estimates of regression coefficients and their variances, even with misspecification of the structure of the covariance matrix, and loss of efficiency from an incorrect choice of the correlation structure is lessened as the number of subjects gets large (Diggle *et al*. 1994).

Backward stepwise elimination was used for logistic regression analyses and model building (Menard 1995; van Mantgem *et al*. 2003). In backward stepwise elimination, the analysis begins with a saturated model that contains all of the explanatory variables. The variable with the smallest Wald statistic term (Hosmer and Lemeshow 2000; Duncan and Chapman 2003) is selected and tested for significance. If the variable is found to have a P-value greater than 0.05, it is removed and a new, reduced model is fitted to the data. Each variable is examined systematically to see if removing it from the model would significantly cause the overall fit to deteriorate. The fit of the model was tested after the elimination of each variable to ensure that the model still adequately fit the data. When all of the remaining variables had a P-value less than 0.05, we declared the analysis complete. As a result, the model consists entirely of variables that are statistically significant (Hosmer and Lemeshow 2000).

At each step, the significance of the explanatory variable being removed was tested using the Wald test (Hosmer and Lemeshow 2000; Duncan and Chapman 2003). The Wald test uses Z-statistics calculated by dividing the coefficients by their robust standard error (White 1982; Beck 1996). The Z-statistics were then squared to yield Wald statistics that follow a chi-square distribution with one degree of freedom. Explanatory variables with coefficients not significantly different from zero ($P > 0.05$) were removed from the model. A multiple Wald test was used for categorical variables (Hosmer and Lemeshow 2000). Only variables that were not strongly correlated (correlation coefficient < 0.60) were used in the development of our logistic regression models. Stepwise regression procedures do not prevent correlated explanatory variables from entering the models, so supervision was required (Battaglin *et al*. 2003). Because the GEE procedure was used, deviance statistics were not available and likelihood ratio tests were not possible. Although the likelihood ratio test is recommended for logistic regression, the Wald test is asymptotically equivalent with large sample sizes (Hosmer and Lemeshow 2000).

The Hosmer–Lemeshow goodness of fit test was used to evaluate the fit of the final models to the data (Hosmer and Lemeshow 2000; van Mantgem *et al*. 2003). The test first partitioned the data into groups based on the predicted probability of mortality. We used 10 ordered groups: those with estimated probabilities below 0.1 formed the first group, and each subsequent group had an incremental increase in probability of 0.1, with the highest group having a probability of mortality of 0.9 to 1.0. The sum of the predicted probability of mortality of all trees in a decile was used as the projected number of trees expected to die in that class. Each decile was further divided into two sets, based on the actual observed status of the trees in 2001 (alive, dead) and the number of observed dead trees. If the models are good, then the projected number of dead trees should be close to the observed number of dead trees. The Hosmer–Lemeshow test statistic (HL) was calculated by comparing the observed and expected frequencies of the dead trees in the decile groups. The test statistic has a chi-square distribution with a desirable outcome of non-significance ($P > 0.05$), indicating that the model prediction does not significantly differ from the observed data.

All data analyses were done with S-Plus 2000 (MathSoft 1999). The GEE S-Plus function version 4.13 (Carey 1998) was used to conduct the GEE logistic regression analyses.

Results

Prior to prescribed burning there were 3711 trees on 72 plots in the 12 experimental units to be burned. At the first post-fire examination of the stands, about 1 month after trees resumed growth at all burn units, there were 278 trees with all needles consumed or scorched; all were presumed dead. However, at the end of the first growing season after the burns (fall 1998), 30 of the trees (eight and 22 from fall and spring burns, respectively) with all needles consumed or scorched had regreened (sprouted needles) (Thies *et al*. 2005). These 30 were included with trees that survived the burns, leaving 248 tagged trees designated immediate mortality and 3463 trees classified as alive after the fire and examined and evaluated for this study. Analysis by logistic regression required complete data for each tree included. Of the 3463 trees of interest, records for 48 trees were incomplete: damage to the top prevented measuring a *tree height* ($n = 42$) or tree position prevented obtaining a measurement such as *dbh* ($n = 6$). All logistic regression analyses were conducted on a reduced dataset of 3415 ponderosa pines that survived for at least 1 month after the burns and for which values were available for all variables: fall burn, 1694 trees; spring burn, 1721 trees. Incomplete tree records were examined for a pattern relating to size, condition, location, and season of burn that might inadvertently introduce a bias into the results; none was

Table 3. Variables evaluated by logistic regression and their associated *P*-values ($n = 3415$)

Variable	*P*-value
Morphological variables	
Diameter at breast height	0.4114
Tree height	0.2226
Live crown ratio	0.0001
Damage variables	
Needle scorch proportion	0.0001
Bud kill proportion	0.0001
Ground char severe	0.6742
Basal char severe	0.0001
Basal char minimum	0.1804
Bole scorch proportion	0.0001
Season of burn	0.8061

detected. For comparison purposes, the means and standard errors of continuous variables for trees in the prescribed burn areas classed as survivors or as delayed mortality through fall 2001 are given in Table 2.

The mean litter and duff depth at random points on the unburned experimental units was 5.3 cm (s.e. = 0.33), whereas the mean depth around trees on those units was 8.11 cm (s.e. = 0.20). Differences in litter and duff depth were not significant between stands either around trees ($P = 0.59$) or at random points ($P = 0.50$).

Using a backward stepwise procedure, we were able to successfully build a logistic regression model comprising five tree level descriptors as predictors of tree mortality four growing seasons after the treatment. All of the variables used to build the model and their stepwise *P*-values are given in Table 3. The five significant variables from the logistic regression model, along with their associated coefficients and standard errors, are given in Table 4.

The following Eqn (1) (using coefficients from Table 4) can be used to determine $P(\mathrm{m})$ (the probability of a particular tree dying after a burn):

$$\begin{aligned} \text{LOGIT } P(\mathrm{m}) = &- 2.2545 \\ &- 3.75 \times (\textit{live crown proportion}) \\ &+ 2.08 \times (\textit{needle scorch proportion}) \\ &+ 3.57 \times (\textit{bud kill proportion}) \\ &+ 0.3018 \times (\textit{basal char severe}) \\ &+ 3.45 \times (\textit{bole scorch proportion}) \\ P(\mathrm{m}) = &\ \text{EXP}(\text{LOGIT}[\pi])/ \\ &(1 + \text{EXP}[\text{LOGIT}\{\pi\}]) \end{aligned} \tag{1}$$

Based on suggestions in Kerns *et al.* (2006) and Thies *et al.* (2005), and after the final model was derived, we specifically tested the hypothesis that fire intensity was more important than burn season in determining delayed tree mortality. Because we did not have direct measures of fire intensity, we used the observed result of fire intensity (variables that are measures of tree damage) as a surrogate. After accounting for the five significant fire damage variables (Table 4), we found no evidence of a difference in the probability of a tree dying in spring *v.* fall (Wald statistic = 0.060, $P = 0.8061$).

Table 4. Full model (five variables) logistic regression table for tree mortality after prescribed burns in ponderosa pine stands near Burns, Oregon, with the coefficient and robust standard error (s.e.)

Variable	Coefficient	Robust s.e.
Intercept	−2.2545	0.5261
Live crown proportion	−3.7467	0.8972
Needle scorch proportion	2.0834	0.3450
Bud kill proportion	3.5714	0.5634
Basal char severe	0.3018	0.0505
Bole scorch proportion	3.4466	0.3196

Table 5. Reduced model (two variables) logistic regression table for tree mortality after prescribed burns in ponderosa pine stands near Burns, Oregon, with the coefficient and robust standard error (s.e.)
NA, not applicable

Variable	Coefficient	Robust s.e.
Intercept	−4.4635	NA
Needle scorch proportion	3.3328	0.3153
Bole scorch proportion	6.6203	0.8879

To provide managers with a reduced model more readily applied in the field, we selected two easily measured variables (*needle scorch proportion* and *bole scorch proportion*) from the main model, and logistic regression was used to develop Eqn (2) (using coefficients from Table 5):

$$\begin{aligned} \text{LOGIT } P(\mathrm{m}) = &- 4.4635 \\ &+ 3.33 \times (\textit{needle scorch proportion}) \\ &+ 6.62 \times (\textit{bole scorch proportion}) \\ P(\mathrm{m}) = &\ \text{EXP}(\text{LOGIT}[\pi])/ \\ &(1 + \text{EXP}[\text{LOGIT}\{\pi\}]) \end{aligned} \tag{2}$$

The full model (five variables) had a good fit to the data: HL = 8.64, d.f. = 8, $P = 0.3732$. The full model predicted a total mortality of 542 trees, based on the five variables of damage caused by the prescribed burn. Table 6 illustrates the fit of both models across the range of probability-of-mortality classes. A total of 550 trees died (Table 6). The five-variable model correctly predicted 98.5% (542/550) of the observed mortality.

The reduced model (two variables) also had a good fit to the data (Table 6): HL = 12.05, d.f. = 8, $P = 0.1488$. The reduced model predicted a total mortality of 530 trees, based on the two measured variables of damage caused by the prescribed burn (Table 6). This model correctly predicted 96.4% (530/550) of the observed mortality. We anticipate that for making land management decisions, managers will be concerned with probabilities of mortality greater than 0.60 for

Table 6. Calculated mortality and observed mortality for full model (five variables) and reduced model (two variables) across the range of mortality classes

	Probability-of-mortality classes, mid-point %										Total
	5	15	25	35	45	55	65	75	85	95	
Full model											
Total trees in class (n)	2393	278	162	92	80	61	59	56	80	154	3415
Projected dead (n)	66	39	39	32	36	33	39	42	68	148	542
Observed dead (n)	82	34	41	23	38	33	32	44	70	153	550
Reduced model											
Total trees in class (n)	2315	280	162	130	153	99	82	78	59	57	3415
Projected dead (n)	64	41	40	46	69	54	53	59	50	54	530
Observed dead (n)	80	44	29	43	60	67	56	61	55	55	550

Table 7. Classification table based on the 10-variable saturated model logistic regression using a cutoff of 0.6

Overall rate of correct classification = ([2820 + 300]/3415) × 100 = 91.4%; overall rate of correctly predicting mortality = 300/345 × 100 = 87.0%

Predicted	Observed		
	Alive	Dead	Total
Alive P(m) < 0.6	2820	250	3070
Dead P(m) > 0.6	45	300	345
Total	2865	550	3415

Table 8. Classification table based on the full-model (five variables) logistic regression using a cutoff of 0.6

Overall rate of correct classification = ([2815 + 299]/3415) × 100 = 91.2%; overall rate of correctly predicting mortality = 299/349 × 100 = 85.7%

Predicted	Observed		
	Alive	Dead	Total
Alive P(m) < 0.6	2815	251	3066
Dead P(m) > 0.6	50	299	349
Total	2865	550	3415

Table 9. Classification table based on the reduced-model (two variables) logistic regression using a cutoff of 0.6

Overall rate of correct classification = ([2816 + 227]/3415) × 100 = 89.1%; overall rate of correctly predicting mortality = 227/276 × 100 = 82.2%

Predicted	Observed		
	Alive	Dead	Total
Alive P(m) < 0.6	2816	323	3139
Dead P(m) > 0.6	49	227	276
Total	2865	550	3415

individual trees. Considering the data from only those trees with a probability of mortality greater than 0.60, there was no evidence of a lack of fit of the reduced model to that data (HL = 3.66, d.f. = 3, $P = 0.3007$).

We used classification tables based on a cutoff of 0.60 probability of mortality as a supplemental measure of model fit. Classification tables were prepared for the saturated model (Table 7), five-variable full model (Table 8), and two-variable reduced model (Table 9). The overall rates of correct classification were 91.4%, 91.2%, and 89.1%, respectively. The overall rates of correctly predicting mortality of individual trees were 87.0%, 85.7%, and 82.2%, respectively.

Discussion

The present study demonstrated that probability of delayed mortality of ponderosa pine in prescribed burns in the southern Blue Mountains of Oregon can be predicted with a single model regardless of the burn season. Thies *et al*. (2005) reported that the proportion of trees dying was higher after a fall prescribed burn than after a spring prescribed burn in the six stands examined in the present study. Two mechanisms likely could explain this seasonal difference in tree mortality: (i) differences in the physiological state of the trees owing to the season in which the prescribed burn was conducted; and (ii) seasonal variation in fire intensity due to differences in weather and fuel conditions. The prescription was the same and was met for burns in both seasons, but it appeared that the fall burns were somewhat more intense than the spring burns. Amount of fuel was the same for all treatments, the litter and duff layer averaged 5.3 cm in thickness, and continuity was broken by open patches of gravel and soil. In both seasons, burning was concentrated around the bases of trees and blackened, on average, a little more than half of the area (Thies *et al*. 2005), which resulted in heterogeneous burn intensity and coverage, making it difficult to visually compare units. Although neither fire intensity nor fuel consumption was monitored, indications were that the fall burn was hotter than the spring burn (Thies *et al*. 2005). After accounting for the fire damage variables (Table 2), there was no indication of a difference in mortality between fall burns and spring burns. We interpreted this to mean that trees with similar degrees of damage from either burn season would have about the same probability of delayed mortality. As a result, only one model is needed rather than two separate seasonal models, and it can be based on all trees in the burns ($n = 3415$).

The 10 independent variables included in the analysis fell into six categories: morphological ($n = 3$), crown ($n = 2$), bole scorch ($n = 1$), basal char ($n = 2$), ground char ($n = 1$), and season of burn ($n = 1$). Five variables were significant: one was a morphological variable and four were damage variables.

Morphological variables

Diameter at breast height was tested in the logistic regression but was not significant and thus not included in the model. *Dbh* is an easy-to-measure indicator of properties related to tree size, such as height, bark thickness, and volume of crown. Thus, stem diameter not only directly reflects a tree's relative resistance to cambial damage but also is an important indicator of resistance to crown damage. Other logistic regression models predicting ponderosa pine mortality use a measure of tree size and a measure of fire damage as independent variables (Harrington and Hawksworth 1990; Saveland *et al.* 1990; Harrington 1993; Regelbrugge and Conard 1993; Finney 1999; Stephens and Finney 2002; McHugh and Kolb 2003).

Crown variables

The amount of crown damage to a ponderosa pine is widely considered the most useful predictor of fire-caused mortality. Our results parallel other studies of ponderosa pine that document increased tree mortality with increasing crown scorch or damage (Herman 1954; Wagener 1961; Dieterich 1979; Wyant *et al.* 1986; McHugh and Kolb 2003). That tree mortality is related to crown damage as represented by the proportion of the crown scorched or killed has also been demonstrated for at least seven other species of western conifers (Peterson 1985; Peterson and Arbaugh 1986; Ryan and Reinhardt 1988).

Needle scorch proportion and *bud kill proportion* are slightly different measures of crown damage. *Needle scorch proportion* reflects the proportion of the crown in which the needles are scorched (killed). *Bud kill proportion* reflects the proportion of the crown in which the heat kills both needles and branch buds, a far more serious injury to the tree (Wagener 1961). The surviving buds on trees may not be observable until some months after the fire.

In the present study, as the *needle scorch proportion* increased there was a corresponding increase in the proportion of trees that died (Fig. 1). Our observation that tree mortality varies continuously with *needle scorch proportion* was not consistent with earlier papers reporting threshold levels of damage above which mortality increased dramatically: a threshold of 80% on 1367 trees observed from two wildfires and one prescribed fire (McHugh and Kolb 2003); a threshold of 60% on 235 trees observed from one wildfire (Herman 1954); a threshold of 67% on 210 trees from a prescribed burn (Davis *et al.* 1968); a threshold of 80% on 200 trees observed from one wildfire (Lynch 1959); and a threshold of 90% on 526 trees observed from dormant and growing-season prescribed burns (Harrington 1993). Some of the differences in recorded thresholds among the earlier studies may have resulted from dissimilar scorch-class widths and overlapping of scorch classes near threshold levels, and from the nature of the fires, especially wildfires, where there may have been unreported basal charring or bole damage that contributed to the death of trees. The fact that we found a continuously increasing mortality response to an increasing value for crown scorch may be explained by a larger sample size (1490 trees with some crown scorch from 3415 trees sampled after prescribed burns).

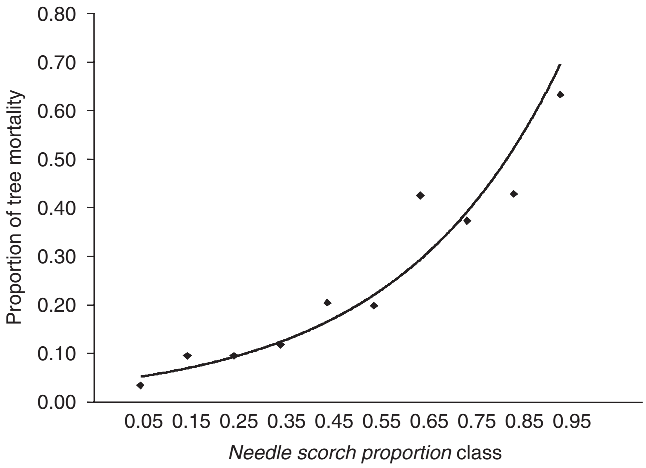

Fig. 1. Proportion of tree mortality by *needle scorch proportion* class.

Bole damage variables

We assumed that damage to the bole was an indication of injury to the cambium, and we recorded variables to evaluate damage at both the base of the tree, measured as *basal char*, and to the bole, measured as *bole scorch* (blackening). Ryan *et al.* (1988) working with Douglas-fir found that the bole damage, expressed as the number of quadrants with dead cambium, is more valuable for predicting mortality than is the proportion of crown volume scorched. We chose to evaluate external damage and did not attempt to measure the amount of dead cambium directly. A direct examination of the cambium would have required further injury to the trees (bark penetration or removal), likely increasing insect attack and potentially altering the outcome of the study. We chose to evaluate visible external damage variables. The only significant *basal char* variable was *basal char severe*, a count of the most damaged quadrants, where the char class was either a '3' (deep char, bark characteristics lost) or a '4' (consumption was complete enough to expose the wood), and was a surrogate measure of the proportion of the circumference of the tree where the cambium was killed by the fire. *Basal char minimum* was a measure of the least-damaged quadrant on each tree and, because we felt a tree could survive with one quadrant intact, was an indication of a tree's ability to survive after a fire. We concluded that the measure of severe damage

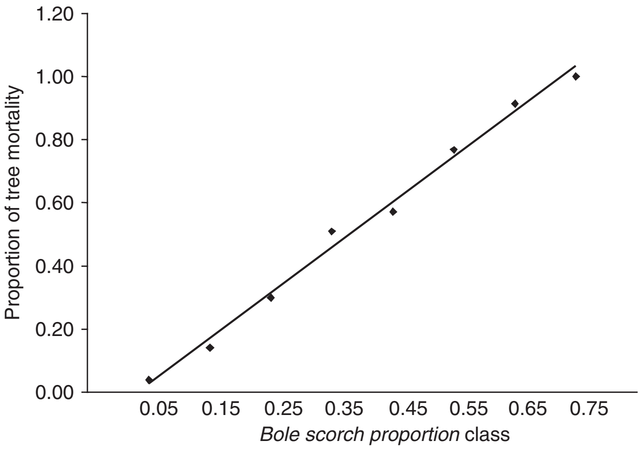

Fig. 2. Proportion of tree mortality by *bole scorch proportion* class.

is a more sensitive indicator of survivability than the measure of minimum damage.

The highest scorch on the bole stated as a proportion of total tree height (*bole scorch proportion*) was significant in the model and was not correlated with other model variables. *Bole scorch proportion* is the same variable that Regelbrugge and Conard (1993) labeled 'relative char height' and also found to be significant in both two-factor and one-factor models. In the present study, as the *bole scorch proportion* increased, there was a corresponding increase in the proportion of the trees that died (Fig. 2).

We anticipated that with higher scorch on the bark would come more heat, and thus an increased likelihood of scorch to the crown. Thus we expected *bole scorch proportion* to be correlated with *needle scorch proportion*, but such was not the case. We speculate that heated air scorching the crown of a tree and the heated air or radiant heat impacting the bole of that tree do not necessarily originate from the same fuel. The prescribed burns in our study were intentionally kept at a relatively low intensity and the burn did not cover the entire area (less than 60% coverage on our plots). As a result, the fire was not uniform and the heat column from the fire was likely to be tilted by any wind, even that generated by the fire or a slope, causing the heat column to scorch the bole of one tree as it moved up to come in contact with the crowns of adjacent trees downwind.

Duff consumption

There is little guidance in the literature for interpreting the effect that duff consumption will have on the increased probability of mortality of ponderosa pine. In general, large ponderosa pine roots will be deep and thus unlikely to be harmed by the consumption of duff; however, Swezy and Agee (1991) provide evidence that duff consumption may injure fine roots of ponderosa pine, which may grow into the duff layer at certain times of the year. Our observations were limited to the area immediately adjacent to the base of the trees. The impact of the duff consumption that we observed is likely to kill cambium. The measure of severe duff consumption (*ground char severe*) was not significant when evaluated in the logistic regression. It is likely that evaluation of the duff consumption immediately adjacent to the tree is a duplication of the evaluation of basal char and does not provide additional information. We speculate that an evaluation of the impact of duff consumption in a broader area, perhaps out to the drip-line of the tree, may provide a useful guide to the impact of duff consumption on tree mortality.

Of the five significant variables used in the full model, one addresses a pre-burn condition, two reflect damage to the crown, and two reflect damage to the bole. Use of the full five-factor model will yield the most accurate prediction of post-burn delayed mortality, but a reduced model is proposed to simplify field application. We propose that a two-variable model to predict delayed mortality of trees observed shortly after a prescribed fire should include *needle scorch proportion* and *bole scorch proportion*. Both variables were significant in the primary model, are easily and consistently measured with a minimum of subjective judgment, do not require that an observer approach each tree (thus saving field time), were used in earlier models, and occurred to some degree on most trees in the burn units. Of 3415 trees on the burn units, only 117 lacked both bole and crown scorch; of these, one died by fall 2001. The other three variables are equally significant in the full model but would be less convenient or easy to measure in the field:

- *Live crown proportion* – the lower limit of the pre-fire live crown is often not easy to identify given that some needles may be consumed and some may fall off before the survey;
- *Bud kill proportion* – to measure the limit of the bud kill requires that the observer wait until the crowns have had a chance to regreen; this delay may not be desirable depending on the timing of other activities and, depending on the tree, regreening is not always easy to see; and
- *Basal char severe* – to make this evaluation the observer must walk up to and around every tree, thus increasing the time required to do a survey.

The two-variable reduced model was almost as good at predicting tree mortality as the five-variable full model (96.4% and 98.5%, respectively). It is likely that a manager would mark for removal only those trees with more than 60% probability of predicted mortality. The reduced model fits the data well in the range of 60–100% probability of mortality. The reduced model offers an adequate estimate of tree mortality that is easier to obtain than one based on the full model.

Several variables were considered but not included in the analysis reported here because they were highly correlated with *dbh* (such as *diameter at stump height* and *bark thickness*) or one class of the variable was so infrequent as to make the predictive relationship meaningless (such as *bark color* and *needle compliment*).

Conclusions

Two models have been developed for predicting the delayed mortality of ponderosa pine following a prescribed fire conducted in either the fall or spring. Either the full or the reduced model should prove useful for projecting delayed mortality in stands that have received a prescribed burn. These models should be useful to managers planning post-burn salvage operations and to ecologists interested in the role of prescribed fire in determining the structure of forest communities. The process involved in fire-caused mortality of trees is still poorly understood. Better understanding of the relationships between fire damage to individual trees and the injury to those trees will improve our ability to predict delayed mortality in prescribed burns and wildfires alike.

We found that ponderosa pine mortality from similar prescribed burns was higher after fall burns than after spring burns. We concluded that this was because dryer fuels and burn conditions caused the fall burns to be somewhat more intense even though the fire plan was to keep the intensity low. We concluded that the mortality is related to the damage inflicted on each tree rather than the season, as mortality relates to the physiological state of the trees. Care should be exercised in extrapolating results and using these models beyond the geographical area of the sampled stands or to species other than ponderosa pine until additional datasets are available to validate the models for other areas or species.

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