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Validating the Malheur model for predicting ponderosa pine post-fire mortality using 24 fires in the Pacific Northwest, USA

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Abstract. Fires, whether intentionally or accidentally set, commonly occur in western interior forests of the US. Following fire, managers need the ability to predict mortality of individual trees based on easily observed characteristics. Previously, a two-factor model using crown scorch and bole scorch proportions was developed with data from 3415 trees for predicting the probability of ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.) mortality following prescribed fire. Here, we report validation of that model for broader application using data from 10 109 ponderosa pines in 17 prescribed fires and 7 wildfires, observed for 3 years post-fire, from east of the Cascade Range crest in Washington, Oregon and northern California. The overall rate of correct classification was 87.1% and the rate of correctly predicting mortality was 80.1%. Similar accuracy is reported when testing the model for small trees (<53.3-cm diameter at breast height), wildfire, prescribed fire, and when using a field guide that simplifies application of the model. For large trees (≥53.3-cm diameter at breast height), the overall rate of correct prediction was 93.6% and the rate of correctly predicting mortality was 65.2%. These results suggest the Malheur model is useful for predicting ponderosa pine mortality following fires in this region.

Additional keywords: Blue Mountains, delayed mortality, large trees.

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Introduction

Ponderosa pine is a commercially and ecologically important tree species in the western United States that grows in forests subject to frequent fires. Considering fire is important in understanding the ecology and management of ponderosa pine and these links have been previously reviewed (Barrett 1979; Baumgartner and Lotan 1988; Agee 1993; Vance *et al.* 2001). Many ponderosa pine stands are currently outside their historic fire return interval. These conditions are commonly attributed to decades of fire exclusion and suppression, timber harvesting and historical periods of overgrazing (Weaver 1943; Covington and Moore 1994; Kolb *et al.* 1994). Prescribed and wildland fire are often used to manage dry western interior forests of the USA. Following fire, the ability to quickly predict tree mortality is essential to evaluate success of burning prescriptions and to provide information to improve future fire prescriptions. Mortality predictions can also be used to better plan post-fire treatments such as hazard tree removal, timber harvest and planting.

Predicting fire-caused mortality

Significant effort has gone into developing tools to predict delayed mortality of fire-injured ponderosa pine. Comprehensive literature reviews of fire-caused mortality (McHugh 2001) and of methods to predict mortality (Fowler and Sieg 2004) of ponderosa pine in the western United States 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 observable external tree injury. Three studies report discriminant analysis models from prescribed fire (Wyant and Zimmerman 1983; Wyant *et al.* 1986; Swezy and Agee 1991), and a comprehensive review of logistic regression models to predict post-fire mortality of conifers is available (Woolley *et al.* 2012). Logistic regression models specifically for predicting ponderosa pine mortality following fire have been developed with data from prescribed fires (Harrington and Hawksworth 1990; Saveland *et al.* 1990; Harrington 1993; Stephens and Finney 2002; Thies *et al.* 2006; Breece *et al.* 2008), wildfires (Regelbrugge and Conard 1993; Finney 1999; Keyser *et al.* 2006; Sieg *et al.* 2006) and a combination of wildfires 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 for predicting mortality. Ryan and Amman (1994) updated the Ryan and Reinhardt (1988) model to use crown scorch and a term for diameter at breast height (DBH) that broadened the model's applicability to include other species including ponderosa pine. There is general agreement that tree size, bole injury and crown injury are useful descriptors for predicting delayed post-fire mortality of trees. However, because a variety of methods have been used to evaluate fire-related injury, there is no consensus on the precise variables to use for predicting mortality (Fowler and Sieg 2004; Hood *et al.* 2010; Woolley *et al.* 2012).

There are relatively few previously published models that have been validated for their accuracy in predicting the delayed fire-caused mortality of ponderosa pine. The updated model by Ryan and Amman (1994) has been validated for ponderosa pine. Weatherby *et al.* (1994) used 243 trees in a wildfire in Idaho; Finney (1999) used 1750 trees in three wildfires in Montana, and Hood *et al.* (2007) conducted a more intensive and extensive validation using data from 14 803 trees of 13 coniferous species from 21 fires in Arizona, California, Idaho, Montana and Wyoming. The sample included 7004 yellow pine, defined as a combination of ponderosa and Jeffrey pine (*Pinus jeffreyi* Grev. & Balf.). Hood *et al.* (2007) concluded that although the model accuracy is good for overall mortality and general planning, it is less accurate for predicting individual tree mortality, and suggested that species-specific mortality models may be more accurate than generalised models that include species-specific terms. Other models were developed and validated for ponderosa pine with data from that species. Regelbrugge and Conard (1993) collected data from trees on one wildfire in California, randomly selected a subset of the sample trees to develop a model and used the rest to validate the model. Keyser *et al.* (2006) used the same process to develop and evaluate a model with data from one wildfire in South Dakota. Sieg *et al.* (2006) developed a model using data from 5083 ponderosa pines from four wildfires, one in each of four states (Arizona, Colorado, South Dakota and Montana), and validated it with data from 1361 trees from one wildfire in South Dakota. Breece *et al.* (2008) used data from 994 trees in four fires in Arizona to validate models developed by McHugh and Kolb (2003) and McHugh *et al.* (2003) based on crown injury and insect attack and reported them to be moderately successful at predicting tree mortality. Hood *et al.* (2010) used data from ponderosa pine in five wildfires in California to validate the Stephens and Finney (2002) model and the survival criteria of Wagener (1961).

Malheur model

In 1996, we initiated a study to examine the influence of season of burn on the appearance of black stain root disease in ponderosa pine (*Pinus ponderosa* Dougl. ex Laws.) following prescribed fire in six mixed-age ponderosa pine stands near Burns, Oregon. Each stand was subdivided and three treatments ($\geq$15 ha each) were applied: spring burn, fall (autumn) burn and no burn (control). Units were burned during mid-October of 1997 or mid-June of 1998. Six circular sampling plots were located in each burn. Trees were tagged and evaluated each fall from 1998 through 2001for status (live or dead). Trees alive in July 1998 ($n = 3415$) were evaluated for 31 tree morphology and fire injury variables that had been reported previously by others (Herman 1954; Ryan 1983; Wyant and Zimmerman 1983; Dixon *et al.* 1984; Wyant *et al.* 1986; Harrington 1987, 1993; Harrington and Hawksworth 1990; Regelbrugge and Conard 1993). Details are available regarding site, stand structure, fire

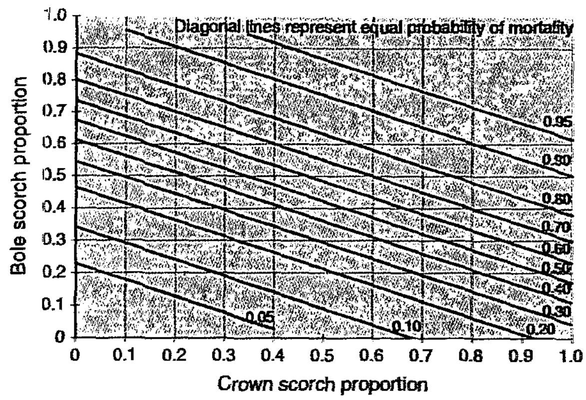

Fig. 1. Malheur model mortality-probability calculator for ponderosa pine. The diagonal line nearest the intercept point of the tree's bole and crown scorch proportions represents the probability of mortality for that tree 3 years post-fire.

treatments and understorey vegetation (Thies *et al.* 2005; Kerns *et al.* 2006).

Measures of crown, bole and basal injury, and tree morphology from the 12 spring and fall prescribed fires were evaluated by logistic regression to develop models for predicting probability of post-fire delayed mortality of individual ponderosa pines (Thies *et al.* 2006). Backward stepwise elimination was used for logistic regression analyses and model building (Menard 1995; Hosmer and Lemeshow 2000; van Mantgem *et al.* 2003) to model individual tree mortality. The resulting full model contained five statistically significant ($P \leq 0.0001$) variables. In order to reduce the amount of time needed to collect data in the field and provide a model convenient to use, two easily measured variables were selected (crown scorch proportion and bole scorch proportion) from the main model, and logistic regression was used to develop the Malheur model (Eqn 1).

$$\begin{aligned} \text{LOGIT}\,P(\text{m}) &= -4.4635 + 3.33 \times (\text{crown scorch proportion}) \\ &\quad + 6.62 \times (\text{bole scorch proportion}) \\ P(\text{m}) &= \text{EXP}(\text{LOGIT}(\pi))/(1 + \text{EXP}(\text{LOGIT}(\pi))) \end{aligned} \tag{1}$$

The Malheur model was presented in graph form (Fig. 1) as part of a one-page field guide (Thies *et al.* 2008), similar to the nomograph presented by Ryan *et al.* (1988, p. 197). The field guide provides a gauge for determining proportion of crown and bole scorch, and instructions for using the gauge and graph (mortality-probability calculator) to determine probability of delayed fire-related mortality of ponderosa pine.

Objectives

Our objectives for this study were to: (1) test the accuracy of the Malheur model to predict delayed mortality of individual ponderosa pines throughout the region using data collected from 10 109 trees (after wildfires and prescribed fires) independently of the prescribed fires used to develop the model; (2) test the

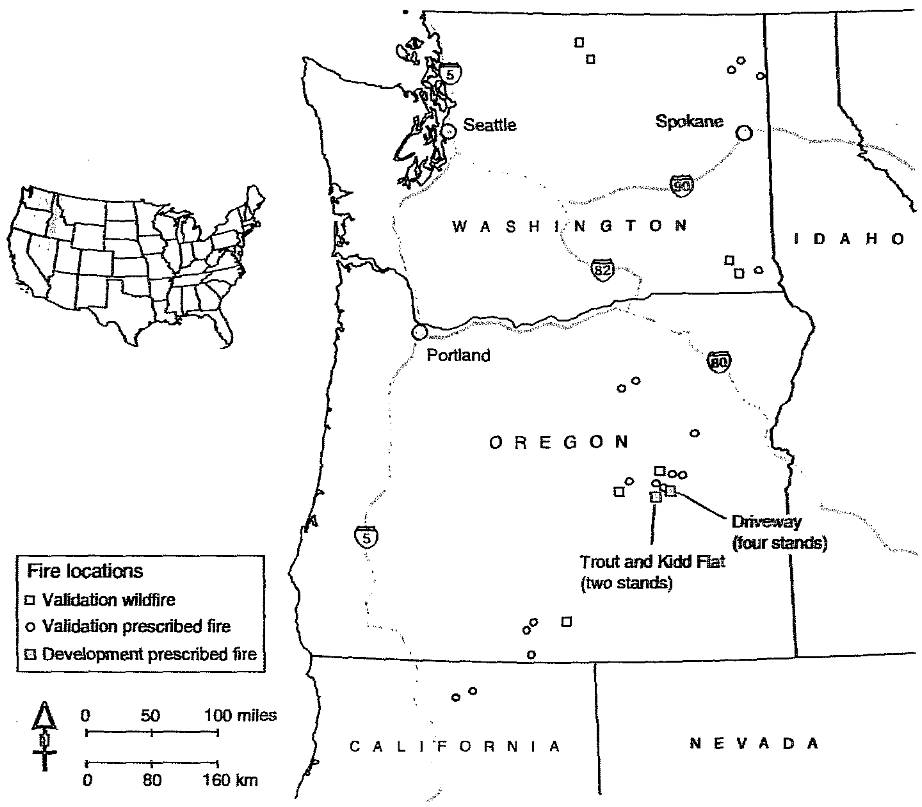

Fig. 2. Location of fires used to collect the Malheur model development and validation data.

accuracy of the Malheur model for predicting tree mortality regardless of fire type (wildfire, prescribed fire); (3) determine if the field guide is an acceptable alternative to using a laser hypsometer to measure variables for the Malheur model; and (4) test the validity of the Malheur model for predicting the mortality of large (≥53.3-cm DBH) ponderosa pines. Results reported in this paper are a continuation and expansion of the validation previously reported by Thies *et al.* (2008) and are intended to replace the preliminary results presented there.

Methods and materials

Validation sites

Validation data were collected for trees on 24 fires (17 prescribed fires and 7 wildfires) from six north-western USDA National Forests (NF): Colville, Fremont–Winema, Klamath, Okanogan–Wenatchee, Malheur and Umatilla (Fig. 2). Local managers selected at least two fires per NF based on availability of staff to participate in data collection and the absence of planned management activities that would interfere with the study. Selected fires burned between fall 2002 and summer 2007. Most fires were identified and data collection initiated within a month following the fire. Three fires in the late fall were not examined until early the next spring. Because of the opportunistic nature of post-fire selection, direct observations of fire behaviour characteristics, such as flame length, are not available.

Sampling

Data were collected from an unbiased sample of fire-injured ponderosa pine. Bias was avoided by including and tagging all standing trees ≥7.5-cm DBH within a 10 m-wide strip-transect of random origin and direction along a road or fire boundary. Each transect continued until a fire boundary was reached, offset 90° 50 to 100 m, and continued along the back azimuth, resulting in a series of parallel transects within the burned area. Sampling was limited to areas of moderate fire severity where tree crowns were not totally consumed but where there was some evidence of fire in the understorey vegetation. Transects in prescribed fires were randomly placed so that all trees within the fire had an equal opportunity to be selected. Sample size varied between sites owing to fire size and available resources. A total of 10 109 trees were evaluated.

Data collection

Diameter at breast height was measured to the nearest 0.25 cm on the uphill side 1.37 m above mineral soil for tagged trees. The distribution of diameters in the sample is presented in Fig. 3. Each tree was evaluated and noted as either alive (if the tree had some green needles) or dead (if all needles were consumed or scorched owing to heat from the fire). Dead trees were categorised by time of death as prefire mortality (based on bark condition, presence of decay and lack of needles and fine twigs), immediate mortality (alive at the time of the fire but dead when

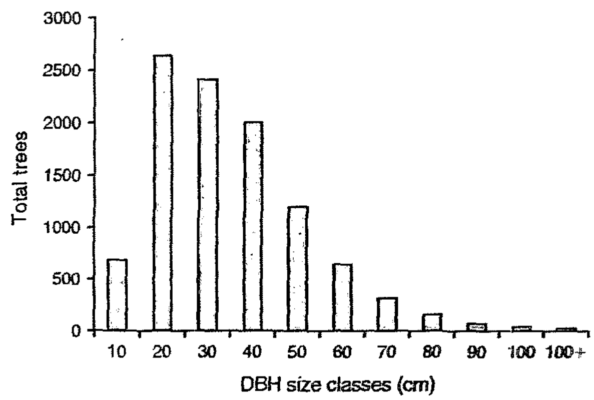

Fig. 3. Frequency by diameter at breast height (DBH) class of live ponderosa pines prefire in the validation dataset ($n = 10\,109$).

tagged) and alive. Trees considered as 'prefire mortality' were not included in the validation evaluation.

Data were recorded for each tree to calculate the two measures of fire-caused injury used in the Malheur model: crown scorch proportion and bole scorch proportion. Crown scorch proportion is the proportion of injured crown length based on scorched or consumed needles. Foliage that exhibited a change in colour as a result of the fire, but was not consumed, was considered to be scorched. The total crown length is the bole length from the tree tip to the lower height of prefire live crown (whorl of three or more live branches). Immediately post-fire, crowns that are alive but injured show two layers: an upper green layer and a lower brown layer of scorched or consumed needles. Injured layers often were asymmetrical. The scorch height was taken as the average height for that injury layer measured at the bole. Bole scorch proportion is the maximum bole scorch height as a proportion of total tree height. Bole scorch is the length of the bole from the forest floor to the highest point of bole blackening. The total tree height, height of prefire live crown, crown scorch height and the maximum bole scorch height were measured to the nearest 3.0 cm with a laser hypsometer. Status (live or dead) of each tree was recorded annually near the end of the growing season for 3 years following the fire. Trees without green needles more than 1 year after the burn were considered dead. A summary of tree data by fire is provided in Table 1.

Data analysis

All statistical analyses were conducted using *SAS 9.2* (SAS Institute Inc. 2008). Crown and bole scorch proportions were calculated for each tree and used to generate a mortality probability using the Malheur model. We evaluated agreement between mortality predicted by the model and the mortality observed using three methods to examine binary response data: (1) tables of the predicted and observed mortality by probability classes; (2) the receiver operating characteristic (ROC) area under the curve (AUC); and (3) classification tables (Hosmer and Lemeshow 2000).

Observed and predicted tables are created by listing the mortality predicted by the model with the actual mortality observed within each of 10 probability groups or deciles based on the calculated probability of mortality from 0.0 to 1.0. Each decile is identified by its probability midpoint (from 0.5 to 0.95). This allows direct comparison of the predicted with the observed mortality throughout the range of mortality probabilities.

The ROC analysis paralleled that used by Saveland *et al.* (1990) to evaluate models of tree mortality following fire injury. The ROC curve is a plot of the proportion of correctly predicted mortality (sensitivity) on the y axis and $1 -$ the proportion of correctly predicted survival (specificity) on the x axis over all possible mortality probability values. The AUC is a measure of a model's ability to discriminate between dead and live trees. The ROC AUC values range from 0 to 1.0: values ≤ 0.5 indicate no discrimination, values ≥ 0.7 are acceptable, values ≥ 0.8 are excellent, values ≥ 0.9 are indicative of outstanding discrimination (Hosmer and Lemeshow 2000).

Classification tables compare the observed outcome with a predicted outcome based on the estimated mortality probability (Hosmer and Lemeshow 2000). To do this, a cutpoint probability of mortality is selected. If the estimated probability exceeds the cutpoint, the tree is predicted to die; if the estimate is less than the cutpoint, the tree is predicted to live. We used a cutpoint probability of 0.50 because it was used previously for fire-injured ponderosa pine (Regelbrugge and Conard 1993; Keyser *et al.* 2006; Hood *et al.* 2007; Hood *et al.* 2010) and for Douglas fir (Ryan *et al.* 1988), and is considered the most common cutpoint for a variety of applications (Hosmer and Lemeshow 2000).

Field guide evaluation

Efficacy of the field guide form of the Malheur model (Thies *et al.* 2008, p. 8) was tested by having the tagged trees from 12 of the validation fires (Table 1) evaluated by two different crews using either instruments or the field guide and comparing the results. One crew (instruments) used a laser hypsometer and calculated the probability of mortality as part of the overall Malheur model validation effort. To assure consistency in the data, this crew was given training to recognise fire injury and supervised by the same crew leader each year. The other crew (field guide) used the field guide. Members of this crew were experienced forestry technicians but did not receive specific training beyond the instructions given in the one-page field guide (Thies *et al.* 2008, p. 8). There was no overlap of members on the crews.

Results and discussion

Evaluation of the Malheur model

A model remains little more than a hypothesis until it is validated with data other than the development data. Such validations provide insights on the general applicability of a model and provide bounds to the geographic and biologic areas of applicability. The Malheur model evaluates the probability of mortality for individual ponderosa pine following a fire. Summary information to compare the development and validation datasets is provided in Table 2. A total of 10 109 ponderosa pines from 24 fires were tagged, measured and observed for mortality for three growing seasons post-fire. Overall, the model predicted a total mortality in validation fires of 2408 trees compared with an observed mortality of 2550, a difference

Table 1. Summary of the location, elevation, precipitation, fire date, fire type, tree status (live or dead), mean diameter at breast height (DBH) and Receiver Operating Characteristic (ROC) score for model fit for the 24 validation fires sorted by % mortality

National Forests are: Um, Umatilla; Fr, Fremont–Winema; Ma, Malheur; Co, Colville; Ok, Okanogan–Wenatchee; Kl, Klamath. Fire types are: WF, wildfire; Rx, prescribed fire. AUC, Area Under the Curve.

Fire name	Latitude, longitude	National Forest	Mean elevation (m)	Mean annual precipitation (cm)	Fire date	Fire type	Trees alive at time of fire (*n*)	Mean DBH (range) (cm)	Trees dead 3 years post-fire (*n*)	Mortality (%)	ROC AUC
Skookum	44°N, 118°W	Ma	1554	56.11	Fall 2002	Rx	497	39.2 (8.9–104.6)	13	2.6	0.765
Gabe	44°N, 118°W	Ma	1615	49.57	Fall 2004	Rx	300	43.2 (10.4–95.0)	17	5.7	0.863
Burnt Valley10[A]	48°N, 117°W	Co	1006	70.38	Fall 2006	Rx	200	54.1 (22.9–99.1)	12	6.0	0.697
Burnt Valley 4[A]	48°N, 117°W	Co	1036	72.39	Fall 2006	Rx	235	39.6 (11.2–79.5)	15	6.4	0.759
Geophysical[A]	48°N, 117°W	Co	762	82.53	Fall 2006	Rx	297	35.9 (7.9–74.9)	21	7.1	0.937
Mallory[A]	45°N, 119°W	Um	1341	55.81	Fall 2006	Rx	494	25.4 (7.6–89.9)	44	8.9	0.831
Curry Springs 1	43°N, 119°W	Ma	1676	54.95	Fall 2002	Rx	109	33.8 (12.2–101.8)	10	9.2	0.744
Curry Springs 2	43°N, 119°W	Ma	1646	53.15	Spring 2003	Rx	213	36.9 (8.6–95.0)	22	10.3	0.749
Black Rock 2	43°N, 118°W	Ma	1707	47.03	Fall 2004	Rx	294	24.1 (7.6–96.5)	35	11.9	0.831
Tennant 1	41°N, 121°W	Kl	1463	63.57	Fall 2004	Rx	731	39.1 (7.9–192.0)	91	12.4	0.937
Black Rock 1	43°N, 118°W	Ma	1676	49.57	Fall 2004	Rx	298	27.8 (8.9–85.1)	42	14.1	0.902
Lick[A]	46°N, 117°W	Um	1402	70.57	Fall 2006	Rx	444	26.0 (6.9–113.5)	66	14.9	0.870
Tennant 2	41°N, 121°W	Kl	1646	60.16	Fall 2004	Rx	359	34.9 (8.6–142.5)	71	19.8	0.892
Mitten[A]	42°N, 120°W	Fr	1829	60.09	Fall 2006	Rx	743	31.0 (7.4–112.3)	159	21.4	0.797
Squaw Meadow	44°N, 118°W	Ma	1646	78.72	Fall 2004	Rx	300	24.6 (7.6–76.4)	80	26.7	0.894
Stateline[A]	42°N, 120°W	Fr	1707	56.25	Fall 2006	Rx	749	28.9 (4.3–75.2)	211	28.2	0.877
Owen[A]	42°N, 120°W	Fr	1524	48.13	Spring 2007	Rx	750	22.4 (7.6–99.1)	219	29.2	0.902
Gravel 17	43°N, 118°W	Ma	1554	43.23	Summer 2007	WF	908	27.3 (7.6–113.5)	308	33.9	0.927
Okanogan 2	48°N, 120°W	Ok	1067	58.07	Fall 2006	WF	521	21.9 (7.1–76.5)	200	38.4	0.892
Bear[A]	42°N, 120°W	Fr	1920	63.28	Fall 2006	WF	262	38.8 (8.1–99.8)	101	38.6	0.934
Sheep Creek[A]	46°N, 117°W	Um	1097	98.06	Fall 2006	WF	146	27.0 (7.4–104.6)	72	49.3	0.935
4712 Road[A]	46°N, 117°W	Um	975	102.11	Summer 2006	WF	135	28.5 (7.1–94.5)	67	49.6	0.901
Okanogan 1	48°N, 120°W	Ok	1341	58.71	Fall 2006	WF	640	23.3 (5.8–125.5)	339	53.0	0.915
Monument[A]	44°N, 119°W	Um	1006	41.12	Summer 2007	WF	484	20.3 (7.1–82.6)	334	69.2	0.889

[A]Fires for which the probability of mortality for sample trees was evaluated by two methods of applying the Malheur model: (1) by collecting the scorch proportion data with instruments and using these data with the Malheur model (Thies *et al.* 2006) to estimate probability of delayed mortality; and (2) by estimating scorch proportions with the field guide and using this with the guide's mortality probability calculator to estimate probability of delayed mortality (Thies *et al.* 2008).

Table 2. Summary of the development and validation datasets

Variable ranges are in parentheses

	Sample size (*n*)	Dead 3 years post-fire	Mortality percentage	Mean DBH (cm)	Mean height (m)	Mean crown scorch proportion	Mean bole scorch proportion	Mean mortality probability
Validation data entire set	10 109	2550	25.2	30.0 (7.5–192.0)	15.5 (1.6–59.4)	0.38 (0.0–1.0)	0.19 (0.0–1.0)	0.24 (0.01–0.99)
Validation data subsets								
Prescribed fire	7013	1128	16.1	31.9 (7.5–192.0)	16.4 (2.7–42.9)	0.30 (0.0–1.0)	0.15 (0.0–1.0)	0.16 (0.01–0.99)
Wildfire	3096	1422	45.9	25.5 (7.5–125.5)	13.4 (1.6–59.4)	0.57 (0.0–1.0)	0.29 (0.0–1.0)	0.41 (0.01–0.99)
Small tree (<53.3 cm)	9155	2475	27.0	26.2 (7.5–53.1)	14.1 (1.6–38.9)	0.40 (0.0–1.0)	0.20 (0.0–1.0)	0.25 (0.01–0.99)
Large tree (≥53.3 cm)	954	75	7.9	65.7 (53.3–192.0)	28.7 (11.3–59.4)	0.16 (0.0–1.0)	0.12 (0.0–1.0)	0.09 (0.01–0.99)
Development data[A]	3415	550	16.1	27.8 (7.5–109.2)	14.1 (2.7–41.7)	0.26 (0.0–1.0)	0.14 (0.0–0.86)	0.16 (0.01–0.99)

[A]From Thies *et al.* (2006).

Table 3. Ponderosa pine mortality predicted and observed using the Malheur model, 3 years post-fire by probability-of-mortality classes for the model development and validation datasets with validation data subsets for fire type, field guide evaluation and tree size

	Probability-of-mortality classes, midpoint										Total
	0.05	0.15	0.25	0.35	0.45	0.55	0.65	0.75	0.85	0.95	
Development dataset[A]											
Total trees in class	2315	280	162	130	153	99	82	78	59	57	3415
Predicted 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
Validation dataset											
Total trees in class	5634	1001	571	479	354	368	358	343	375	626	10 109
Predicted dead (*n*)	186	143	142	166	159	203	232	257	319	601	2408
Observed dead (*n*)	258	117	145	199	174	212	250	267	329	599	2550
Validation data subsets – fire type											
Prescribed fire subset											
Total trees in class	4608	716	377	300	216	185	160	152	132	167	7013
Predicted dead (*n*)	148	102	94	103	97	102	103	114	112	160	1137
Observed dead (*n*)	188	69	86	113	101	96	105	110	109	151	1128
Wildfire subset											
Total trees in class	1026	285	194	179	138	183	198	191	243	459	3096
Predicted dead (*n*)	37	41	48	62	62	101	129	143	207	441	1271
Observed dead (*n*)	70	48	59	86	73	116	145	157	220	448	1422
Field guide evaluation											
Instruments											
Total trees in class	2681	507	282	258	202	184	169	166	190	296	4935
Predicted dead (*n*)	86	72	71	89	91	102	109	125	162	284	1191
Observed dead (*n*)	159	63	92	116	102	102	118	122	164	283	1321
Field guide											
Total trees in class	2595	498	320	236	197	150	180	155	246	358	4935
Predicted dead (*n*)	73	76	83	86	91	84	119	118	210	343	1284
Observed dead (*n*)	187	72	84	80	84	75	107	103	190	339	1321
Tree size											
Large tree subset (≥53.3 cm)											
Total trees in class	760	86	34	20	8	10	9	5	12	10	954
Predicted dead (*n*)	20	12	8	7	4	6	6	4	10	10	87
Observed dead (*n*)	20	5	10	6	4	3	4	3	12	8	75
Small tree subset (<53.3 cm)											
Total trees in class	4874	915	537	459	346	358	349	338	363	616	9155
Predicted dead (*n*)	165	132	134	159	156	197	226	254	309	591	2323
Observed dead (*n*)	238	112	135	193	170	209	246	264	317	591	2475

[A]From Thies *et al.* (2006).

of 5.6%. These results closely parallel the model's accuracy in predicting mortality for the model development fires (Table 3). There is close agreement between the mortality predicted by the Malheur model and that observed within each probability class, especially those above 0.05. The ROC AUC is 0.903 (95% confidence interval from 0.896 to 0.910) ($n = 10109$), indicating an outstanding fit between predicted and observed. The classification table (Table 4) shows that using a cutpoint mortality probability of 0.50, the Malheur model has an overall correct classification rate of 87.1% and a correct mortality prediction rate of 80.1%.

A comparison of predicted and observed mortality (Table 3) indicated that the model is most accurate at mortality probability classes over 0.05. Some trees in all classes die for reasons unrelated to fire, such as mechanical injury from wind and snow, disease, or stress related to a specific microsite. Mortality unrelated to fire will not be predicted by the model. For the lowest mortality probability class (0.05) of the validation dataset, 186 trees were predicted to die and 258 were observed dead out of a population of 5634. This 72-tree difference between predicted and observed mortality represents ~1.3% of the class total. This is similar to the 1.0% non-fire related mortality observed in the unburned control portion of the

Table 4. Classification table based on the Malheur model prediction of tree mortality for the full validation dataset using a cutpoint of 0.50
Overall rate of correct classification = ([7146 + 1657]/10 109) × 100 = 87.1%; overall rate of correctly predicting mortality = (1657/2070) × 100 = 80.1%. *P*(m), probability of mortality

Predicted	Alive	Observed dead	Total
Alive $P(m) < 0.5$	7146	893	8039
Dead $P(m) > 0.5$	413	1657	2070
Total	7559	2550	10 109

Table 5. Classification tables for validation data subsets based on the Malheur model to predict tree mortality using a cutpoint of 0.50
P(m), probability of mortality; DBH, diameter at breast height

Predicted	Observed Alive	Observed Dead	Observed Total
Prescribed fires			
Overall rate of correct classification = ([5660 + 571]/7013) × 100 = 88.9%; overall rate of correctly predicting mortality = (571/796) × 100 = 71.7%			
Alive P(m) < 0.5	5660	557	6217
Dead P(m) > 0.5	225	571	796
Total	5885	1128	7013
Field guide			
Overall rate of correct classification = ([3307 + 843]/4935) × 100 = 84.1%; overall rate of correctly predicting mortality = (843/1150) × 100 = 73.3%			
Alive P(m) < 0.5	3307	478	3785
Dead P(m) > 0.5	307	843	1150
Total	3614	1321	4935
Trees < 53.3 cm DBH			
Overall rate of correct classification = ([6283 + 1627]/9155) × 100 = 86.4%; overall rate of correctly predicting mortality = (1627/2024) × 100 = 80.4%			
Alive P(m) < 0.5	6283	848	7131
Dead P(m) > 0.5	397	1627	2024
Total	6680	2475	9155
Wildfires			
Overall rate of correct classification = ([1486 + 1086]/3096) × 100 = 83.1%; overall rate of correctly predicting mortality = (1086/1274) × 100 = 85.2%			
Alive P(m) < 0.5	1486	336	1822
Dead P(m) > 0.5	188	1086	1274
Total	1674	1422	3096
Instruments and the Malheur model			
Overall rate of correct classification = ([3399 + 789]/4935) × 100 = 84.9%; overall rate of correctly predicting mortality = (789/1004) × 100 = 78.6%			
Alive P(m) < 0.5	3399	532	3931
Dead P(m) > 0.5	215	789	1004
Total	3614	1321	4935
Trees ≥ 53.3 cm DBH			
Overall rate of correct classification = ([863 + 30]/954) × 100 = 93.6%; overall rate of correctly predicting mortality = (30/46) × 100 = 65.2%			
Alive P(m) < 0.5	863	45	908
Dead P(m) > 0.5	16	30	46
Total	879	75	954

original study (Thies *et al.* 2005). In classes above the 0.05 probability of mortality (Table 3), the predicted and observed mortality are in close agreement.

Type of fire

The Malheur model had a good fit of the predicted to the observed mortality for both wildfire, $n = 7$, and prescribed fire, $n = 17$ (Table 3). The ROC AUC indicates an excellent fit between predicted and observed mortality for both fire types: 0.871 (95% confidence interval from 0.858 to 0.884, $n = 7013$) for prescribed fires, and 0.909 (95% confidence interval from 0.899 to 0.920, $n = 3096$) for wildfires. The classification tables for prescribed fire and wildfire indicate a good fit, with correct classification rates of 88.9 and 83.1% respectively and correct rates of predicting mortality of 71.7 and 85.2% respectively (Table 5).

Our results show that the ROC AUC and the rate of correctly predicting mortality are higher for wildfires than for prescribed fires and that higher overall mortality rates will result in higher ROC AUC scores. As the mortality rate increases, the percentage of trees with higher mortality probabilities increases. Models are most accurate when there is the least uncertainty about the outcome. Trees with a 0.95 mortality probability will be accurately predicted to die in ~95% of the cases whereas trees with a 0.50 probability will only be accurately predicted to die in 50% of the cases. This results in an increase in the ROC AUC and in the correct classification rate for predicting mortality as the mortality rate increases. In our validation dataset, all wildfires had higher mortality rates than the prescribed fires, 46 and 16% respectively, but this will not always be true. Some wildfires are slow-moving ground fires causing little injury, and some prescribed fires burn at high intensity, resulting in severe injury. Because fire type and mortality rate are so closely correlated in our dataset, we cannot completely address the issue of fire type. Once the effect of mortality rate is considered, it appears that each tree responds individually to its fire-related injury regardless of fire type. A similar conclusion regarding levels of fire injury was reached by Thies *et al.* (2006) and by Woolley *et al.* (2012).

Field guide evaluation

The field guide can be used as a reliable tool for predicting delayed mortality of ponderosa pine in this region because it predicted mortality results comparably with using instruments such as the laser hypsometer (Table 3). The field guide ROC AUC was 0.857 (95% confidence interval from 0.844 to 0.871, $n = 4935$) whereas the instrument ROC AUC curve for the same trees was 0.885 (95% confidence interval from 0.873 to 0.896, $n = 4935$). The classification tables for the field guide evaluation and for the instrument evaluation (Table 5) show overall rates of correct classification of 84.1 and 84.9% and correct rates of mortality classification of 73.3 and 78.6% respectively.

The field guide was developed to reduce the time required to gather data and provide an evaluation in the field. Users must decide if the benefits outweigh the slight reduction in predictive accuracy. A likely application scenario is using the laser hypsometer or similar instrument for measuring scorch heights and calculating scorch proportions and using the mortality probability calculator portion of the field guide (Fig. 1) to determine mortality probabilities.

Tree size

The Malheur model did well in predicting the delayed mortality of large and small ponderosa pine for all probability-of-mortality classes (Table 3). The ROC AUC for small trees (<53.3-cm DBH) is 0.902 (95% confidence interval from 0.894 to 0.910, $n = 9177$). The ROC AUC for large trees (≥53.3-cm DBH) is lower, 0.834 (95% confidence interval from 0.772 to 0.896, $n = 954$), but still shows excellent discrimination. The classification table for small trees (Table 5) shows an overall rate of correct classification of 86.4% and a rate of correctly predicting mortality of 80.4%. The table for large trees shows an overall rate of correct classification of 93.6% with a rate of correctly predicting mortality of 65.2%.

As a matter of policy, large trees currently are being protected or being given special consideration in Region 6 (Pacific Northwest) of the USDA Forest Service and are of special concern to managers in that area (USDA Forest Service 1995). Large trees were present in all model development and validation fires and the mortality rates were similar, 7.0 and 7.9% respectively. The validation fires contained 954 large trees, of which 75 were observed dead and 87 were predicted to die. The large trees were not given special treatment or protection in any of the fires.

A plot of % mortality by 10-cm DBH classes (Fig. 4) shows declining mortality rates with increasing diameter through the 55–65-cm DBH class. The rate of mortality increases slightly in the DBH classes above 65 cm. Others have reported a distinct U-shaped mortality distribution following fires, with smaller- and larger-diameter trees having much higher mortality rates than mid-diameter trees (Swezy and Agee 1991; McHugh and Kolb 2003; Kolb *et al.* 2007). Although we observed an increase in mortality in DBH classes over 65 cm ($n = 555$), the % mortality was considerably less than that reported by Kolb *et al.* (2007, fig. 1). We speculate that we are observing the same trend but from the perspective of a larger sample of each diameter class. On our sites, we did not observe as much increase in % mortality at the largest DBH classes as reported

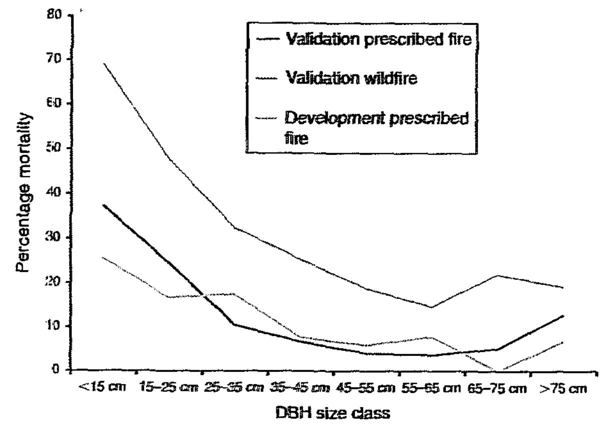

Fig. 4. Observed mortality of ponderosa pine in the development and validation datasets by diameter at breast height (DBH) class. Validation prescribed fire: includes trees from 17 prescribed fires from the validation dataset ($n = 7013$); validation wildfire: includes trees from the wildfires in the validation dataset ($n = 3096$): includes trees from the 12 prescribed fires in the model development dataset ($n = 3415$).

by Kolb *et al.* (2007). Although our mortality rates differ, a slight U-shaped mortality distribution is evident for both prescribed fires and wildfires (Fig. 4). We agree with others that the observed increased mortality likely has two primary causes: (1) higher fuel buildup at the base of large trees causes higher temperatures for longer times, resulting in more root and cambial injury at the base of the tree (Ryan and Frandsen 1991; Finney 1999; McHugh and Kolb 2003), and (2) injured cambium can attract phloem-feeding bark beetles, causing additional mortality (Finney 1999; Kelsey and Joseph 2003; McHugh and Kolb 2003). The sites in the present validation vary in the numbers of large trees. Fire histories for our sites are not well known but none appear to have burned in recent times and there was duff buildup around the base of the larger trees. Basal injury may not be well captured by the two variables in the Malheur model and could explain why it does not perform quite as well for large trees. The Malheur model does not include DBH as a factor because it was not found to be a significant predictor of fire-related mortality (Thies *et al.* 2006). If mortality is a U-shaped function of diameter as suggested by our data and that of Kolb *et al.* (2007), then including diameter in a logistic model would be inappropriate (Hosmer and Lemeshow 2000).

Application

The Malheur model was developed for land managers as a simple, accurate, easy-to-use tool for predicting post-fire mortality of ponderosa pine. Both crown scorch and bole char proportion were selected for use in the model based on predictive ability, ease of measurement and their availability for measurement immediately post-fire. Other measures of injury to tree crown and bole are available but they did not meet our selection criteria. Bud kill may be a good predictor of pending mortality but in the case of late-spring and summer fires, it is not evident until new growth starts the following spring. Crown consumption is difficult to identify, especially by field crews without extensive experience. Measuring cambium kill is time-consuming and adds additional injury to each tree. The model was developed in a relatively small geographic area using data from 3417 ponderosa pine on 12 prescribed fires at the south end of the Blue Mountains near Burns, Oregon. The validation reported here tested model accuracy using data from ponderosa pine in stands, unrelated to the development stands, from six NFs east of the Cascade Range crest from near the Canadian border south through Washington and Oregon and into northern California. This large geographic area encompasses a variety of environmental conditions (Fig. 2, Table 1). Because the model predicted well for each of the 24 validation stands, we conclude that the Malheur model has broad applicability. The model has been shown to accurately predict tree mortality status regardless of season of burn (Thies *et al.* 2006), type of fire (wildfire or prescribed fire), elevation, latitude, year of fire and mean annual rainfall (see Table 1 for ranges). The environmental breadth of stand conditions where the model performed well further supports the broad use of the Malheur model for ponderosa pine forests east of the Cascade Crest. As with any predictive model, caution is advised when applying the Malheur model outside the range of stand conditions used in model development and validation.

Anomalies

No model predicts delayed mortality perfectly. Other variables not measured may be important and the trees occasionally do not respond as predicted. For example, in the fires used for model development, there were 278 trees recorded to have a crown scorch proportion of 1.0, yet 30 survived one season and 20 (7.2%) of those survived more than three seasons. In the validation fires, 1834 trees were recorded to have a crown scorch proportion of 1.0, yet 156 (8.5%) were still living 3 years post-fire. What might be termed background mortality not caused by the fire was also apparent. In the model development dataset, there were 117 trees lacking both bole and crown scorch, and one died within 3 years post-fire. Similarly, in the validation dataset, 368 trees lacked both bole and crown scorch and five of those died within 3 years post-fire.

Validation sampling caution

Care must be taken in validation sampling in order to avoid overstating the prediction accuracy for the model being tested (Thornes and Stephenson 2001). Following fires, especially wildfires, some areas will have a majority of trees with 100% crown scorch and high percentages of bole scorch and crown consumption. For these trees, a model predicting mortality is of little value because most forest managers would predict that they will die and do not need the aid of a statistically based model to help make that decision. If a large number of these easy-to-predict (likely dead) trees are included in a validation effort, the reported rates of correct mortality prediction will be exaggerated. For example, our validation dataset with an overall mortality rate of 25.2 has an excellent fit with an ROC AUC value of 0.903, a correct classification rate of 87.1%, and a correct rate of predicting mortality of 80.1% ($n = 10\,109$). Suppose, for example, that we had not limited ourselves to areas of moderate fire severity and included an additional 10 109 trees that were killed immediately by the fire and have a probability of mortality of 0.999. Our overall mortality rate would be 62.6% and the results are far better with an ROC AUC value of 0.981, a correct classification rate of 93.5%, and a correct rate of predicting mortality of 96.6% ($n = 20\,218$). This example is extreme but illustrates the effect that sampling has on reported fit statistics. In selecting which mortality model(s) to use, managers will need to carefully evaluate the sampling methods used in the model development and validation. For this effort, we limited the sampling to areas that received moderate fire severity because these are the areas where forest managers will need the model as an aid in making post-fire management decisions.

Conclusions

(1) There is good agreement between the delayed mortality of ponderosa pine predicted by the Malheur model and the mortality observed 3 years following a fire.
(2) The Malheur model accurately predicts the probability of fire-related delayed mortality of individual trees in both prescribed fire and wildfire.
(3) The field guide for determining probability of mortality of ponderosa pine is an effective tool that can be used by forestry technicians with little or no special training.
(4) The Malheur model can be used to determine the probability of fire-related mortality of ponderosa pine between 7.5- and 192.0-cm DBH.
(5) The breadth of the validation sampling and the number of stands in which the model accurately predicted mortality supports use of the Malheur model beyond the development and validation stands.

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