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Applying survival analysis to managed even-aged stands of ponderosa pine for assessment of tree mortality in the western United States

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ABSTRACT

A critical component of a growth and yield simulator is an estimate of mortality rates. The mortality models presented here are developed from long-term permanent plots in provinces from throughout the geographic range of ponderosa pine in the United States extending from the Black Hills of South Dakota to the Pacific Coast. The study had two objectives: estimation of the probability of a tree survival for the next 5 years and the probability of a tree surviving longer than a given time period (survival trend) for a given set of covariates. The probability of a tree surviving for the next 5 years was estimated using a logistic model regressed on 18 covariates measured 5 years before the last measurement period with 15 smoothing variables (S1–S15) for spatial effects of latitude and longitude surface. The fitted model showed that the probability of survival increased with increasing diameter at breast height (DBH), DBH periodic annual increment (PAIDBH) and increasing plot basal area/number of trees per hectare (PBAH/TPH), and decreased with increasing average of the 5 tallest trees in the plot (AVGHT5) when other selected covariates were included in the model. The probability of a tree surviving longer than a given time period was estimated by fitting the Cox Proportional Hazard model to the last observed survival period regressed on 13 covariates measured at the first measurement period. This probability also increased with increasing DBH and PAIDBH, and decreased with increasing AVGHT5. The Akaike's Information Criterion (AIC) and graphs of partial residuals were used in the selection of covariates included in the models.

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1. Introduction

Competition among trees is one of the main factors determining their growth and mortality (Oliver and Uzoh, 1997; Zeide, 2004). The competition stressors can be long-term or short-term (van Mantgem et al., 2003). For a model to adequately characterize tree growth it must include estimates of mortality rates (or survival), because mortality is an integral part of stand dynamics (Monserud, 1976; Hamilton, 1986; Hann and Wang, 1990). The literature on modeling tree mortality is voluminous; nevertheless, mortality estimates remain the weakest link in growth and yield simulators because of estimation difficulties (Hamilton, 1986). There are two main causes of tree mortality: external and internal factors. Mortality resulting from external factors tends to be episodic and often even catastrophic, especially if mortality is a result of factors such as bark beetles, root disease, or wind. Mortality resulting from internal factors arises from inter-tree competition and it tends to be more uniform and constant (Oliver and Uzoh, 1997).

The first generation of statistical mortality models was at the stand level, predicting the future number of trees per unit area (Lee, 1971; Moser, 1972; Ek, 1974; Somers et al., 1980; Clutter et al., 1983; Harms, 1983). Subsequently, Hamilton (1974) and Monserud (1976) introduced the use of logistic regression models for individual tree mortality response.

Survival analysis is a recent improvement in assessing mortality trends and dynamics of individual trees. Woodall et al. (2005) provided a superb history and reason for the use of survival analysis in modeling tree mortality. In general, survival analysis is a collection of statistical procedures for data analysis used for studying the occurrence and timing of events for which the outcome variable of interest is most often death, which was the purpose for their original designs (Kleinbaum and Klein, 2005; Woodall et al., 2005; Allison, 2010). The uniqueness of survival analysis stems from the fact that it allows for censoring of observations (lack of exact time of death) and inclusion of time-dependent covariates, and dealing with non-normal distributions (Woodall et al., 2005). These features of survival data make it difficult to handle with commonly-used conventional statistical methods, but ignoring them will reduce the precision of the estimates (Allison, 2010).

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Consequently, conventional approaches such as Logistic regression are inadequate for dealing with either censoring or time-dependent covariates, something at which survival analysis excels (Allison, 2010).

Kleinbaum and Klein (2005) defined two quantitative terms that should be considered in any survival analysis. These are the survivor function, denoted by $S(t)$ and the hazard function denoted by $h(t)$ for the survival time t. The survivor function $S(t)$ gives the probability that an individual (in our case, a tree) survives longer than some specified time t: that is, $S(t)$ gives the probability that the random variable T exceeds the specified time t (Kleinbaum and Klein, 2005; Woodall et al., 2005; Allison 2010). The hazard function focuses on failing, that is, on the event occurring because the hazard function $h(t)$ gives the instantaneous potential per unit time for death to occur, given that the individual has survived up to time t. In contrast the survivor function focuses on not failing, that is, on the event not occurring. In a unique sense, both functions can be considered as giving the opposite side of the information given by the other (Kleinbaum and Klein, 2005).

We used two survival modeling approaches in our investigation: the logistic regression (parametric approach, McCullagh and Nelder, 1991) for 5-year responses, and the Cox Proportional Hazard, regression (semi-parametric approach, Cox, 1972, 1975; Lee and Wang, 2003) for censored responses.

The objective of this study is to develop an individual tree mortality model applicable for even-aged pure stands of ponderosa pine throughout its geographic range in the United States. The objective is divided into two phase: (1) to build a survival model for predicting the probability of a tree surviving to the next 5 years based on plot/tree information measured 5 years before the last measurement period and (2) to build a survival model to estimate the probability of a tree surviving longer than a given time period based on plot/tree information at the first measurement period. The Cox PH model here is used as an explanatory model but not as a predictive model, because of its non-parametric distribution assumption for the survival time. For phase (1), we fitted the Logistic model, and for phase (2), we fitted the Cox Proportional Hazard (PH) model. For both models, we considered the following groups of measured candidate explanatory (predictors) variables:

1. *Plot spatial information*: latitude, longitude, elevation, slope and aspect.
2. *Stand structure information at measurement time*: plot basal area, number of trees per hectare, stand age, average of the five tallest trees in the plot (however, if less than five, then we just calculated their average.), site index, site density index, and basal area per hectare in larger diameter.
3. *Tree information at measurement time*: DBH, DBH periodic annual increment, and tree basal area.

2. Methods

2.1. Data

The measurements were made in years ranging from 1938 to 1998. Some plots were measured repeatedly (for example, 1938–1943–1948–1953; 1963–1967–1971–1979–1984–1989–1994), and others only once or twice. Several datasets used in this study were from long-term permanent plots consisting of: (a) levels-of-growing-stock studies established in the 1960s using a similar study design with five or six stand density levels replicated three times (Myers, 1967) and (b) initial spacing and permanent-plot thinning studies. Individual-tree data were from plots initiated from both artificial stands and natural stands located in the five provinces of ponderosa pine in the western United States (Fig. 1) and initially covering a wide range of size classes. Stands were free, or mostly free, of competing shrubs that reduce growth of young ponderosa pine especially in central Oregon and California (Oliver, 1984; Oliver and Ryker, 1990; Cochran and Barrett, 1999). Results from individual installations of the levels-of-growing-stock studies have been previously reported (Tables 1 and 2), as were growth models based on five installations (Oliver and Edminster, 1988; Uzoh and Oliver, 2006, 2008).

Trees were tagged and repeatedly measured on periods of different length (ranging from 2 years to 18 years lag), but about 68% of the measurement were done every 5 years. Seventy-eight percent of the plots were measured for more than 10 years. The data resulting from this study consisted of 305 plots with a total of 29,449 trees. Of those trees, 28,901 trees were used for fitting the Cox PH model. Some trees had to be removed from the analysis because some plots were measured only once, while at others plots, measurements were done in 2-year interval but not in the same years. Of these, 20,118 trees were used for the logistic model because they were measured in 5-year intervals. Table A1 in the Appendix shows the summary of the original dataset and Table A2 shows a summary of the last 5-year measurement periods. Fig. 2 shows the distribution of mortality within the study area.

Basic records for each plot included latitude, longitude, elevation, aspect, slope percent, and plot size. Individual tree measurements included diameter at breast height (DBH) and total height. Different methods were used at different locations for sampling tree height. At some locations, every tree height in each plot was measured; at others, a systematic sample of tree heights were measured; yet at other locations, height sample trees were randomly selected within 2 in. diameter classes across the range of tree sizes. Height measurements were repeated on the same trees (Uzoh and Oliver, 2006). Mortality was noted and the causal agent investigated. The data for this analysis consists only of the initial, and the last two measurement periods, called from now on "Initial", "Prior" and "Current". The two models (the Logit model and the Cox Proportional Hazard model (Cox PH model)) aim to predict/explain the current survival response with the information from the prior or initial period. Therefore, only the values of the explanatory variables from the initial measurement period, from the 5-year period prior to the last measurement period and the current survival status, are used in this analysis.

Many trees in a number of plots suffered competition-induced mortality. For the Cox PH model, since a tree either died during an interval or is alive at the end of the study and the year of death is unknown, we have a case of interval censoring (Allison, 2010). Some of the measurement periods were of different length, therefore, it is possible that the estimated survival probability has some bias or added imprecision. It is possible that a greater than 10-year time lag between measurements increases the bias or decreases the precision of the estimate, however, only 4.3% of all the 28,901 trees had a time-lag greater than 10 years and of these only 1.2% died in those intervals. We fitted the COX model with these trees removed and the trees and the slopes' trend of the coefficients did not change and the deviance residual plots showed the same pattern as that shown for the whole dataset. As a result, we chose not to remove the trees from the analysis.

2.2. Statistical analyses

2.2.1. Logistic model for predicting 5-year survival probability

We used the Logistic model from the family of the Generalized Additive Models (GAMs) (Hastie and Tibshirani, 1990).

2.2.1.1. Logit model.

$$\log\left(\frac{p}{1-p}\right) = g(LAT, LONG) + \sum_{j=0}^{m} c_j * x_j$$

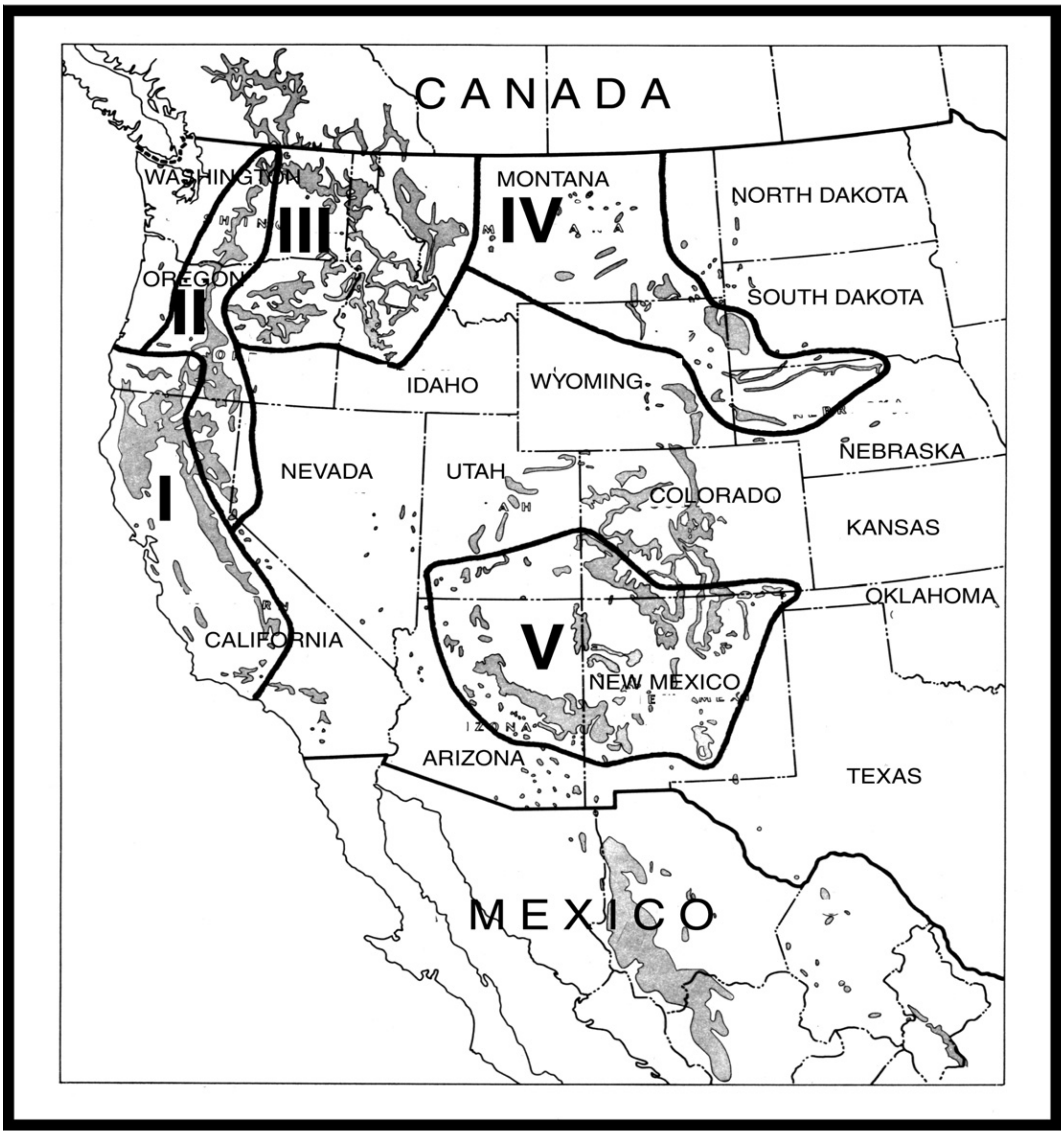

Fig. 1. Study area provinces used in developing the individual tree mortality model for managed even-aged stands of ponderosa pine throughout the western United States (from Myers, 1967).

Table 1
Location and literature citations for five levels-of-growing-stock installations in ponderosa pine stands in western United States.

Province	Installation name	Geographic location	Literature citation
I	Elliot Ranch	West slope northern Sierra Nevada, CA	Oliver (1997)
II	Lookout Mountain	East side of Cascade Range, OR	Cochran and Barrett (1999)
III	Crawford	Blue Mountain, OR Creek	Cochran and Barrett (1995)
IV	Black Hills	Black Hills, SD	Boldt and Van Deusen (1974)
V	Taylor Woods	Coconino Plateau, AZ	Ronco et al. (1985)

where p is the probability that a tree is alive at the end of 5 years from last measurement date; $g(LAT,LONG)$ is a smoothing function of latitude and longitude (to account for the spatial correlation and location effect); c_j is the regression coefficients of the covariates x_j, j = 1 to m, and m is the number of selected covariates. x_0 = 1 and c_0 = intercept term. Since there was almost a one-to-one correspondence between elevation and location (LAT–LONG pair), elevation was not included as a covariate candidate. The variable selection was done using the partial residual graphs for the application of the Generalized Additive Model (GAM, Hastie and Tibshirani, 1990) for the response alive/dead, using the Logit link regressed on spline transformed (smoothed) covariates. The need for parametrically transforming an explanatory variable (polynomial, exponential or logarithmic transformation) was determined after visually observing the partial residual graphs of the spline-smoothing resulting from the application of GAM. The spatial effect was forced in all the candidate models. We used an information theoretical approach to determine the best-supported model for estimating the probability of survival regressed on selected explanatory variables (Burnham and Anderson, 2002). We evaluated candidate

Table 2
Plot distribution in each province by stand origin and tree size used to develop survival analysis model for managed even-aged stands of ponderosa pine throughout the western United States.

Province / Number of plots	I	II	III	IV	V
Stand origin					
Natural	7	81	32	42	18
Planted	92	18	15	0	0
Stand size class					
Saplings	32	30	9	15	0
Poles	58	61	38	27	18
Sawn timber	9	8	0	0	0
Total	99	99	47	42	18

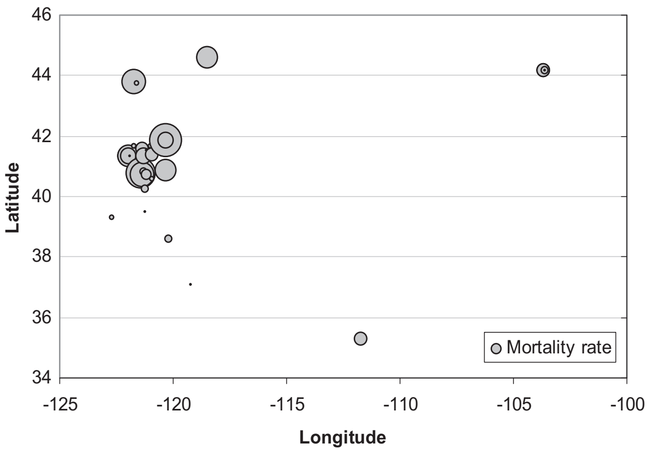

Fig. 2. Latitude and longitude of sampled plots. Showing the distribution of mortality within the study area.

models using Akaike's Information Criterion (AIC) (Rawlings et al., 1998; Hastie et al., 2001; Burnham and Anderson, 2002). The spatial function g was fitted using the tensor product spline techniques (Wood, 2006). Analyses and parameter estimation were conducted using GAM MGCV routine in R (version 2.15.1, 2012). We used the selected model and R for predicting the probability of a tree surviving the next 5-year.

2.2.2. The Cox Proportional Hazard model for survival probability trend

The objective of the analysis is to estimate the tree survival probability trend as a function of tree conditions and plot characteristic. The survival function, $S(t)$, is defined as $S_i(t)$ = Probability that a tree i survives longer than a given time t from diagnosis, with t in 1-year units. The Cox Proportional Hazards model (Lee and Wang, 2003), a semi-parametric survival regression model, was used to model the probability of $S_i(t)$.

2.2.2.1. Cox PH model. The hazard function for interval censored data is modeled as follows:

$$h(t|\mathrm{x}) = h_i(t)EXP\left(\sum_{j=1}^{v} a_j * x_j\right),$$

where $h_i(t)$ is baseline hazard function, that is, it is the underlying hazard function that represents the risk of the tree dying about time t for stratum i; stratum was defined as a categorical variable defined for each latitude–longitude pair at the same initial measurement year. Latitude and longitude were stratified by rounding to the first decimal. Therefore, the survival analysis was done in the "neighborhood" of the Locale (for example, latitude = 35.28, longitude = 111.72 and initial measurement year = 1969, would be stratum: 35.3–111.7–69). The total number of strata is 55. a_j is the regression coefficients and x_j, is the covariate j, j = 1 to v, measured at the initial measurement year and v is the number of selected covariates. Increases in the risk results in lower probability of survival. Since there was almost a unique elevation per LAT–LONG pair, elevation was not included as a covariate candidate. Similarly to the logistic model, we used an information theoretical approach to determine the best-supported model for estimating the probability of survival. To obtain a list of candidate models, we applied the best subset selection method based on the likelihood score statistic on untransformed and transformed explanatory variables used for the logistic model, and then we evaluated some of the apparently best candidate models using Akaike's Information Criterion. The parameter estimation was conducted using the SAS PHREG procedure (SAS 9.2, Cary, North Carolina, USA) for stratified data.

Covariate candidate and notation
1. DBH = tree diameter at breast height,
2. PAIDBH = tree DBH periodic annual increment,
3. PBAH = plot basal area per hectare,
4. TPH = number of trees per hectare,
5. StAGE = stand age,
6. BAINLDH = basal area per hectare in larger diameter,
7. AVGHT5 = average height of the 5 tallest trees in the plot,
8. SIM = site index (Meyer, 1938),
9. SDI = stand density index,
10. SLOPE = plot slope percent,
11. ASP = plot aspect,
12. SLCOSASP = SLOPE ∗ cos(ASP),
13. SLSINASP = SLOPE ∗ sin(ASP),
14. LAT = site latitude,
15. LONG = site longitude,
16. Initial year.

Since SDI was highly correlated with PBAH (Corr = 0.96), we also tried the ratio PBAH/TPH as an explanatory variable instead of PBAH and it was very significant. The transformation enabled us to include SDI in the model. In total, there were 16 candidate variables and possible functions of them such as logarithms or polynomials as explanatory variables, and 20,118 observations for the logistic model and about 28,901 observations for the Cox PH model.

2.3. Model testing and validation

Shugart (1984) defined model validation as "procedures, in which a model is tested on its agreement with a set of observations that are independent of those observations used to structure the model and estimate its parameters." There are many types of model validation procedures used by most practitioners; some are qualitative and others are quantitative (Holmes, 1983; Sargent, 1999). The use of statistical tests in model validation has resulted in vigorous debates following the work of Wright (1972), because of the different criteria used for assessing the value of models and the methods of deciding it (Mayer et al., 1994; Morehead, 1996). Each model is unique; as a result, no single validation technique or method has a monopoly in application (Kozak and Kozak, 2003). For deciding the most suitable model, it is advisable to use a combination of lack-of-fit measures with one or more test statistics (Kozak and Kozak, 2003). Consequently, it is important to know that the goals of model testing and validation are not designed to prove that a model is accurate (Popper, 1963). Rather to see how well the predicted survival probabilities agreed with the observed probabilities and demonstrate that model predictions are statistically and biologically close enough to independent data and that decisions made based on the model are defensible (Yang et al., 2004).

There are five established procedures commonly used in model validation: (1) a comparison of predictions and coefficients with physical theory; (2) a comparison of results with those obtained by theory and simulation; (3) the use of new data set; (4) the use of data splitting or cross validation (Snee, 1977); and (5) a combination of calibration and discriminatory power (Pearce and Ferrier, 2000). Independent data sets are often not available; as a result, most practitioners accept data splitting as an acceptable substitute for model testing and validation, provided that the data set is large enough (Kozak and Kozak, 2003). To validate the Cox PH model, the dataset was randomly split into 10 parts, then 8 of those 10 parts (80%) were used for initial model development and 2 parts (20%) were used for model validation. We repeated this procedure 20 times and obtained an averaged percentage of matches. The final model was developed using the entire dataset. We used spatial latitude and longitude and initial measurement year to account for autocorrelation and location effect. We did not validate the Logistic model because we did enough diagnostics for the goodness of fit.

The logistic model performance was evaluated using a combination of calibration and discriminatory assessment procedures (Pearce and Ferrier, 2000). Calibration assessment procedure examined the R^2 index, percentage of deviance explained, plot of residuals and the reliability diagram to see the model power of predictability and how well the predicted survival probabilities agreed with the observed probabilities. The discriminatory assessment procedures were used to show how well the model was able to discriminate between living and dead trees. Specifically, the receiver operating characteristic (ROC) curve, measured by the area under the ROC curve (AUC) was evaluated by discriminatory visualization of ROC curve (Fielding and Bell, 1997). The ROC curve procedure is a non-parametric and threshold-independent measure developed by plotting sensitivity (all true positive values) against 1-specificity (all false positive values). The ROC curve can be interpreted as the probability that a randomly selected tree that survived the next 5 years had higher probability of survival than a randomly selected tree that died during the same period (Fielding and Bell, 1997).

3. Results

3.1. Predicting 5-year survival probability with the logistic model

The following were the selected covariates: log(DBH), PAIDBH, PBAH/TPH, $[PBAH/TPH]^2$, $[PBAH/TPH]^3$, StAGE, $[StAGE]^2$, $[StAGE]^3$, BAINLDH, $[BAINLDH]^2$, $[BAINLDH]^3$, AVGHT5, SLSINASP, SLCOSASP, SDI, $[SDI]^2$, and $[SDI]^3$ (18 coefficients estimated including intercept). Fifteen smoothing coefficients (S1–S15) were also estimated for the spatial effect as a function of latitude and Longitude. Almost all the estimated coefficients were highly significant (Table 4, R^2 = 0.75, Deviance explained = 67%). To visualize the meaning of the estimated coefficients, we use the partial residuals' graphs from the fitted logistic regression in Fig. 3 that depicted the parametric form of the explanatory variables and their trends. Fig. 3 shows that the probability of surviving (at the logit scale) 5 more years increases with increasing log(DBH) (and therefore, with increasing DBH), PAIDBH and PBAH/TPH. Fig. 3 also shows that the probability of surviving (at the logit scale) 5 more years decreased with increasing SDI, AVGHT5, SLSINASP and SLCOSASP. The decreasing or increasing trend of SLSINASP, SLCOSASP translates as follows: (1) for a constant aspect, if the slope percentage increases then the probability of survival decreases and if the percentage decreases the probability of survival increases and (2) for a constant slope, if aspect increases from East to North, the probability decreases, and if aspect increases from North to West to South, this probability increases (Fig. 6). To illustrate the trend and the explanatory power of some covariates, Fig. 4 shows the plot of the predicted probability of surviving the next 5 years as a function

Table 3
Summary statistics for variables used in developing the individual tree mortality model for managed even-aged stands of ponderosa pine throughout the western United States.

Variable	Mean	Minimum	Maximum
Stand age (years)	66.45	8	110
DBH (cm)	19.58	1.02	98.04
PAIDH (cm)	0.31	0	2.23
PLOTBA (m^2/ha.)	11.05	0.28	30.08
TPH (#trees/ha)	1553.29	44.48	17,173.73
Avg. HT (m)	18.49	3.61	50.28
BAINLDH (m^2/ha)	19.92	0	91.33
SDI (#trees/ha)	576.43	21.18	1,444.22
SIM (m)	21.62	13.11	48.77
SLOPE (percent)	6.16	0	42
ASPECT (degrees)	113.07	0	315
ELEV (m)	1503.79	716.28	2266.19

Table 4
Logistic regression estimated coefficients for the individual tree mortality model for managed even-aged stands of ponderosa pine throughout the western United States, R^2(adj.) = 0.75 and deviance explained = 67%.

Covariate[a]	Estimate	StdErr	P-value
Intercept	7.24	0.60	<0.0001
log(DBH)	1.87	0.13	<0.0001
PAIDBH	3.67	0.36	<0.0001
SLSINASP	−0.24	0.03	<0.0001
SLCOSASP	−0.03	0.01	0.0005
PBAH/TPH	188.60	22.84	<0.0001
$[PBAH/TPH]^2$	22.35	14.69	0.1323
$[PBAH/TPH]^3$	116.80	14.11	<0.0001
StAGE	423.00	18.70	<0.0001
$[StAGE]^2$	260.20	14.49	<0.0001
$[StAGE]^3$	−501.60	20.71	<0.0001
BAILNDH	59.31	9.72	0.0000
$[BAILNDH]^2$	−65.03	6.17	<0.0001
$[BAILNDH]^3$	41.35	6.04	<0.0001
SDI	−113.25	15.85	<0.0001
$[SDI]^2$	−51.33	10.92	<0.0001
$[SDI]^3$	−16.67	9.43	0.0797
AVGDHT5	−0.58	0.02	<0.0001
S1	−19.023	2.171	–[a]
S2	4.398	4.074	–
S3	−77.786	34.164	–
S4	−50.923	34.563	–
S5	54.706	12.447	–
S6	−31.143	8.384	–
S7	−72.276	6.485	–
S8	53.985	21.946	–
S9	−26.973	10.149	–
S10	59.338	17.211	–
S11	80.847	13.755	–
S12	970.103	120.677	–
S13	239.293	76.553	–
S14	135.010	40.048	–
S15	56.411	54.072	–

[a] The overall significance of 15 smooth terms (notated as te.LONG.LAT . . . n, n = 1–15): DF te(LONG,LAT) 14.47, Chi sq. 1352, P-value <0.0001. The 15 coefficients shown in this table are also displayed in Appendix B.

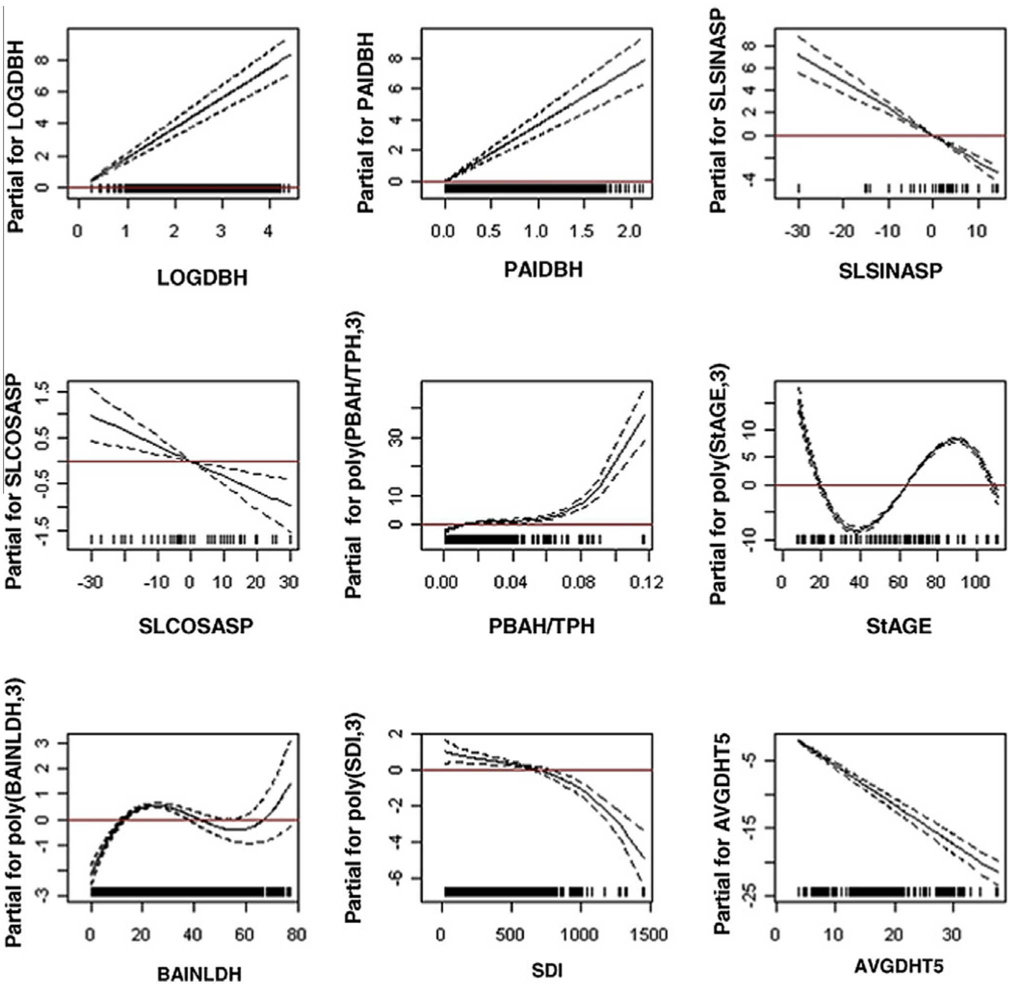

Fig. 3. Partial residuals' graphs from the fitted logistic regression (GAM) for each selected covariates and the 95% confidence interval. The partial residuals for the smoothed latitude–longitude surface is not shown.

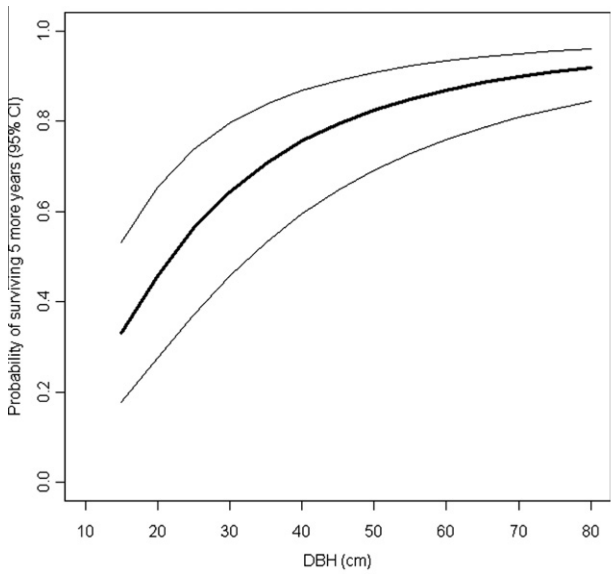

Fig. 4. Example of predicted probability of survival within the next 5 years for ponderosa pines as a function of DBH for a given set of measured covariates 5 years before: LAT = 41.62; LONG = -120.33; PAIDBH = 0.36 cm; aspect = 0, slope = 0%; PBAH = 10 m^2/ha; TPH = 333.3 trees/ha; stand age = 70; BAINLDH = 0.5 m^2/ha; SDI = 615; Av. Ht = 30 m.

Table 5
Estimates of the hazard coefficients output from for Cox PH regression model for strata latitude–longitude and initial year for the individual tree mortality model for managed even-aged stands of ponderosa pine throughout the western United States.

Covariate	Estimate	StdErr	*P*-value
log(DBH)	−1.610	0.045	<0.0001
PAIDBH	−2.133	0.328	<0.0001
St.AGE	0.388	0.100	<0.0001
[St.AGE]2/100	−0.264	0.090	0.0033
AVGHT5	0.040	0.012	0.0005
BAINLDH	−0.042	0.012	0.001
$[BAINLDH]^2$	0.0027	0.0005	<0.0001
$[BAINLDH]^3$	−0.000034	0.000007	<0.0001
SIM	1.534	0.209	<0.0001
$[SIM]^2$	−0.064	0.009	<0.0001
$[SIM]^3$	0.0008	0.0001	<0.0001
PBAH/TPH	111.557	9.942	<0.0001
$[PBAH/TPH]^2$	−561.066	125.171	<0.0001

of DBH for a given set of measured covariates 5 years before. The partial residual graph (Fig. 3) also shows that with increasing BAINLDH from 0 to about 20 the probability of survival increases, then from 20 to 60 it fluctuates down and up and then increases. The partial residuals' graph for the stand age, StAGE, a cubic polynomial, shows that the probability of survival decreases for ages increasing from 0 to about 40 years, then increases from 40 to about 91 and then decreases beyond 91 years.

The fitted logistic model can be used for predicting the next 5-year survival probability. Appendix B shows an example of how to use the output of the fitted model to predict 5-year survival probability of a tree for a given set of covariates including the smoothing covariates (nodes) for latitude and longitude. Appendix B includes the R source code for obtaining the predicted probability of survival and its confidence interval, and the needed data. The needed data are: (1) the 33 estimated coefficient values (18 coefficients for the covariates and 15 for the nodes), (2) the latitude–longitude-nodes matrix (a 42×17 matrix; matrix row has 42 LAT × LONG combinations and the columns are the LAT, LONG and nodes (te.LONG.LAT ... *n*, *n* = 1–15)), (3) the covariance matrix of the estimated parameters (33×33 matrix), and the covariate information for a new tree including its location (LAT and LONG) as an example.

3.2. Survival probability trend

The following were the selected covariates: log(DBH), PAIDBH, StAGE, [StAGE^2], BAINLDH, [BAINLDH]^2, [BAINLDH]^3, AVGHT5,

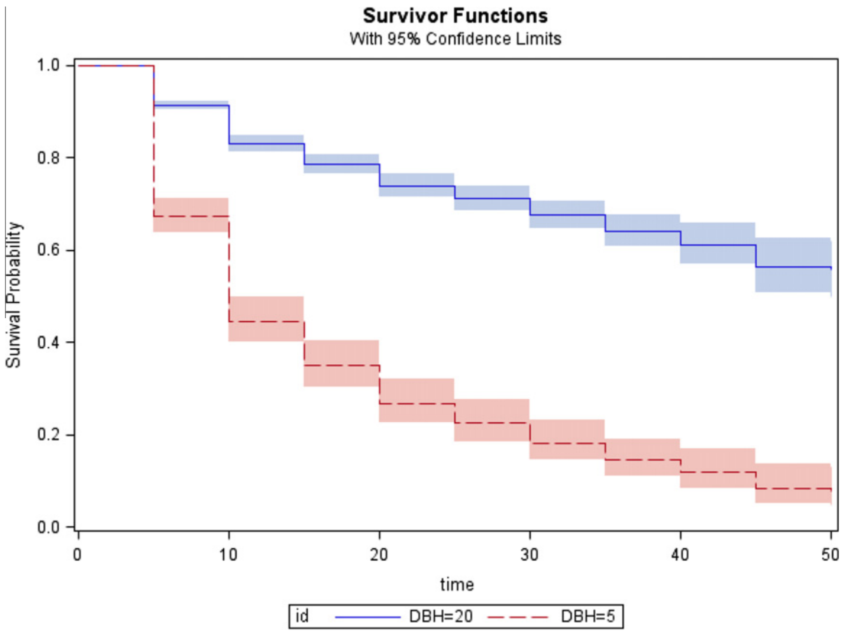

Fig. 5a. Example of predicted probability of survival through time for two ponderosa pines of DBH = 20 cm and DBH = 5 cm, respectively, for a given set of covariates measured on the prior sampling period: stand age = 40 years; PAIDBH = 0.3 cm; PBAH = 10 m^2/ha; TPH = 700 trees/ha; BAINLDH = 15 m^2/ha; aspect = 0; slope = 2%; Av. Ht = 15 m.

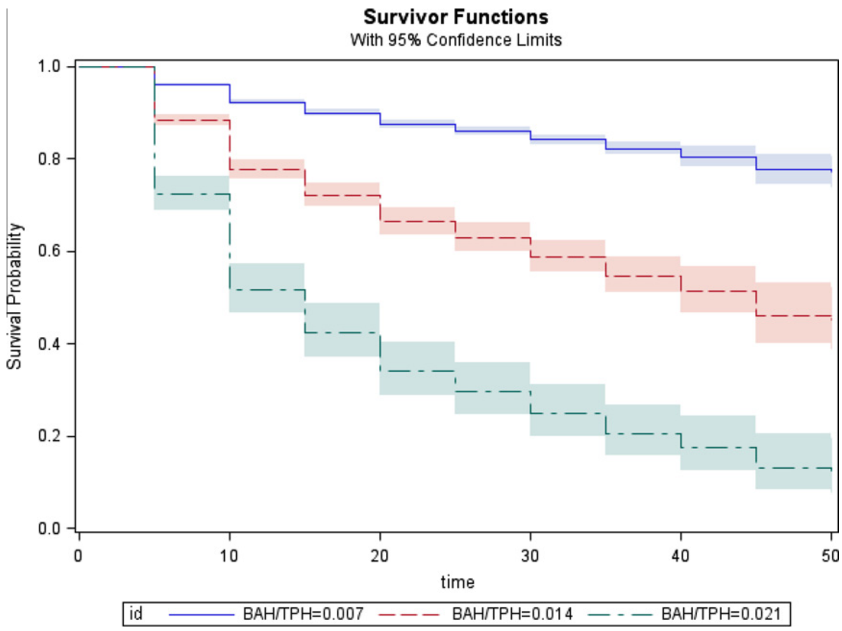

Fig. 5b. Example of predicted probability of survival through time for ponderosa pines for three plot PBAH = 5, 10 and 15 m^2/ha, for a given set of covariates measured on the prior sampling period: DBH = 15 cm; stand age = 40 years; PAIDBH = 0.3 cm; TPH = 700 trees/ha; BAINLDH = 15 m^2/ha; aspect = 0; slope = 2%; Av. Ht = 15 m.

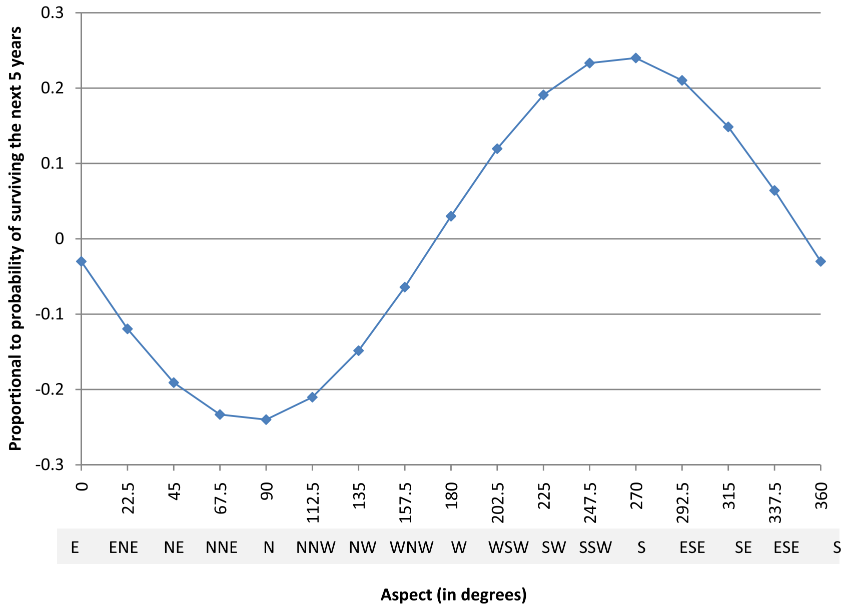

Fig. 6. Function proportional to the probability of surviving the next 5 years at a given aspect (function = $-.03 * \text{Slope} * \cos(\text{aspect}) - 0.24 * \text{Slope} * \sin(\text{aspect})$. Slope is kept constant.

SIM, [SIM]^2, [SIM]^3, PBAH/TPH, and [PBAH/TPH]^2. The estimated hazard coefficients are shown in Table 5. The strata were the most important variables during variable selection using AIC. However, no explicit estimate can be obtained for each stratum because the COX PH model is a semi-parametric model, meaning the survival time does not have a parametric statistical distribution; the stratum is considered to be a nuisance parameter. However, the stratification affects the survival function by making the fit more precise. The explanatory variables were all highly significant. Table 5 shows that the risk of a tree dying decreases with increasing log(DBH) (and therefore, with increasing DBH), and PAIDBH. Table 5 also shows that the risk of a tree dying increases with increasing AVGHT5. Table 5 also shows the estimated coefficients for stand age (StAGE). The coefficient indicates that the risk of a tree dying increases for StAGE in the interval 0 to about 80 years of age and then the risk decreases. Table 5 also shows that for the third degree polynomial of SIM that the risk increased with increasing SIM. Figs. 5a and 5b illustrate the probability of surviving longer than a given time, for given set of explanatory variable values measured at initial measurement period.

3.3. Model performance

Figs. 7 and 8 are summary measures of goodness of fit for the COX PH and the logistic models, showing scatter-plot of deviance

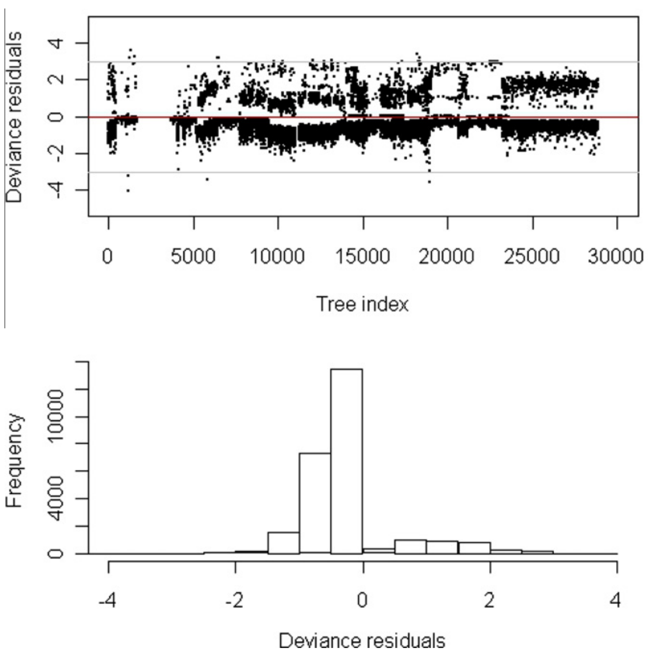

Fig. 7. Summary measures of goodness of fit for the COX PH model: scatter plot of deviance residual against tree index and deviance residual histogram.

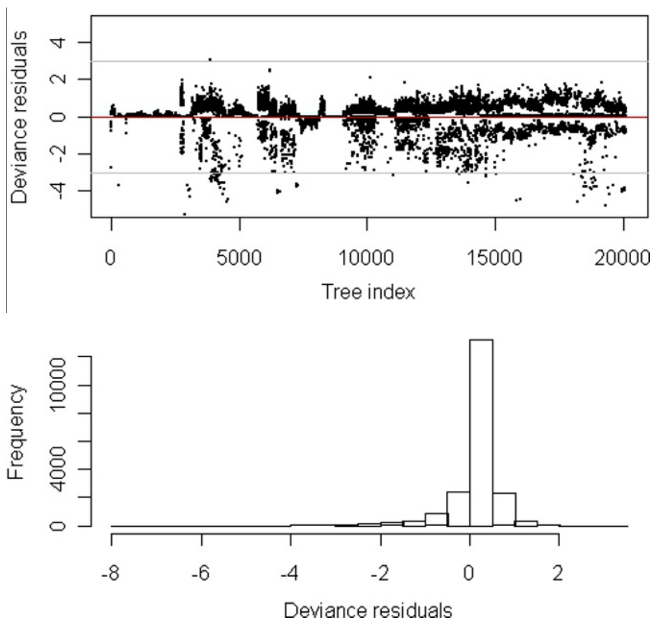

Fig. 8. Summary measures of goodness of fit for the logistic model: scatter plot of deviance residual against tree index and deviance residual histogram.

residuals against tree index, and histograms of deviance residuals. For the survival models, the deviance residuals are not useful for checking the goodness of model fit. It is mainly used to check which points are far away from the rest due to lack of fit, and more or less are within the [−3,3] interval. These residuals are usually plotted against the observation identification; in our case, against an arbitrary tree index. There are relative small numbers of points outside the [−3,3] interval as shown by the histograms in both plots. However, they seem not to diminish the adequacy of the models. The ROC curve of the reduced models appears reliable (Fig. 9) for the logistic model. The bias-corrected (optimism – corrected) discriminatory power of the reduced model yielded an area under the curve (ROC curve) value of 0.9645 (Fig. 9). The assessment methodology developed by Hosmer and Lemeshow (2000) showed that the discriminatory power of the reduced model appear adequate (ROC curve value of 0.9645). Fig. 10 shows the reliability diagram (Bröcker and Smith, 2007) for the logistic model showing the observed survival frequency (dots), predicted probabilities (smooth curve) of survivals, and the individual trees' 95% confidence intervals against the linear predictor describing the agreement of estimated probability with the observed frequency. The observed survival values (dead = 0 or alive = 1) were grouped into 20 classes according to the linear predictor and for each class the frequency (observed proportion) was calculated (Bröcker and Smith, 2007). Overall, the observed proportion seems to agree with fitted probability with the exception of one case in the lower probability. The 20 random validation trials for the Cox PH model showed that the 84% (CI: 79–88%) of the validation points fell within the 95% confidence interval of the survival curve fitted with the model building dataset. Fig. 11 illustrates this validation with four examples. The summary statistics of variables used in developing the individual tree mortality models are presented in Table 3.

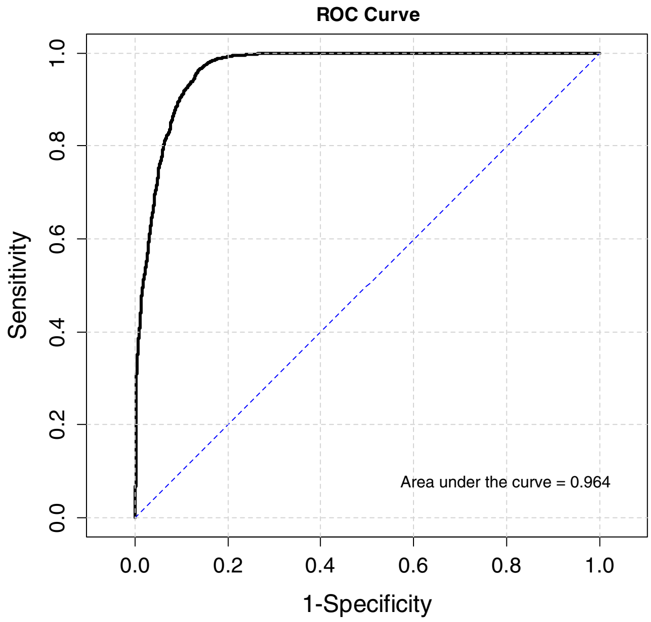

Fig. 9. receiver operating characteristic (ROC) curve for the original data set (reduced model). Sensitivity (all true positive values) against 1-specificity (all false positive values).

4. Discussion

We conducted our analysis in two parts: First, the estimation of the probability of a tree surviving the next 5 years based on plot/tree information using a logistic model regressed on 18 covariates measured 5 years before the last measurement period and 15 smoothing variables (S1–S15) for spatial effects of latitude and Longitude surface (Table 4). Second, the estimation of the probability of a tree surviving longer than a given time period based on plot/tree information at the first measurement period using the Cox Proportional Hazard model regressed on 13 covariates (Table 5). In both analyses, the models showed that the probability of survival increased with increasing diameter at breast height

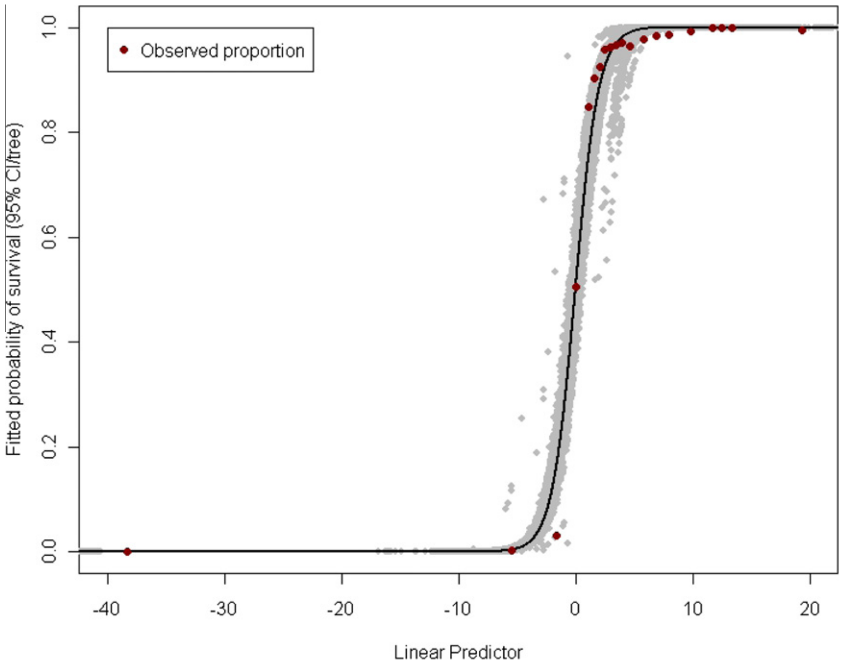

Fig. 10. Reliability diagram for the logistic model showing the observed survival frequency (dots), predicted probabilities (smooth curve) of survivals, and the individual trees' 95% confidence intervals against the linear predictor describing the agreement of estimated probability with the observed frequency. The observed survival values (dead = 0 or alive = 1) were grouped into 20 classes according to the linear predictor.

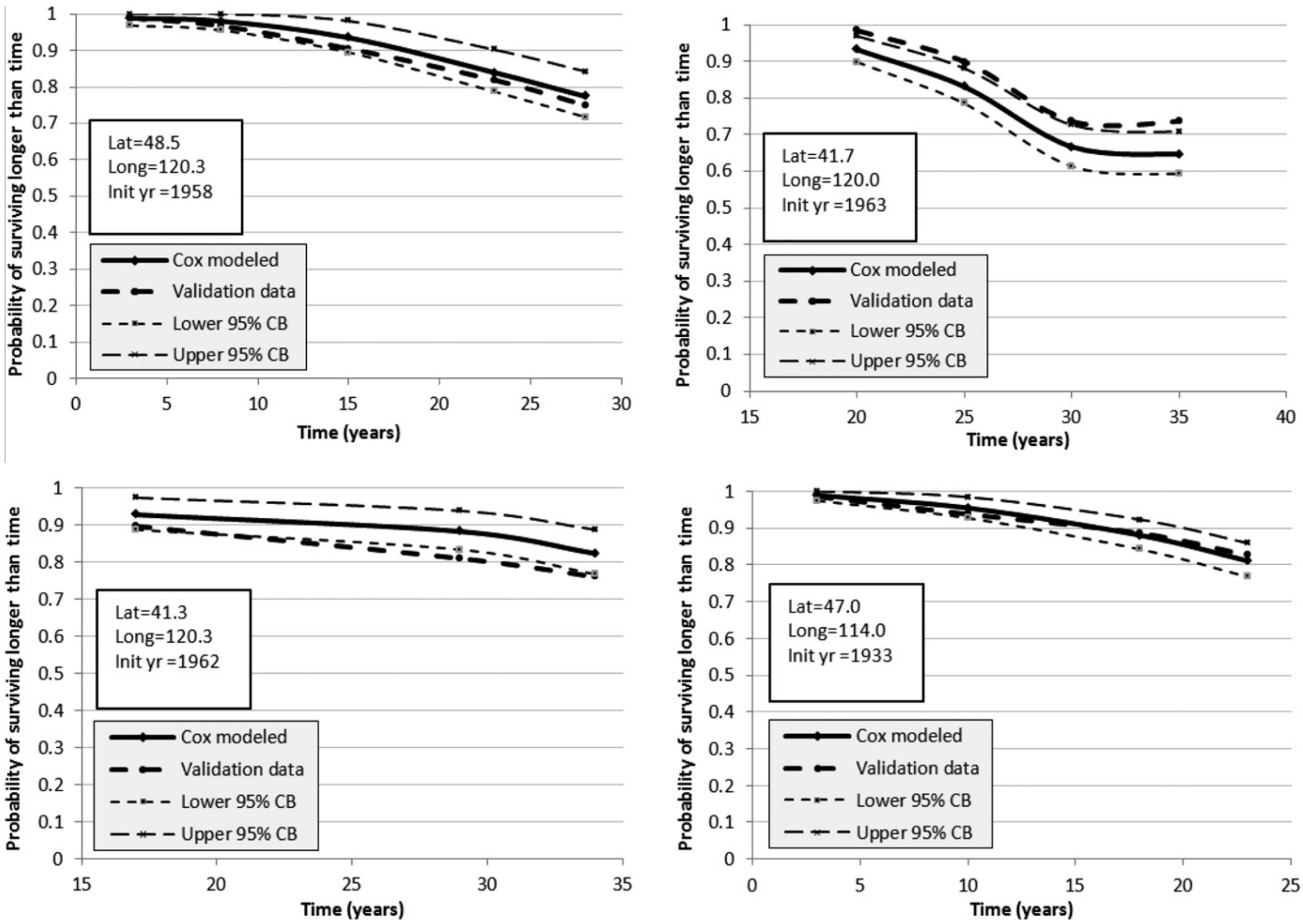

Fig. 11. Validation of the Cox PH model: Four examples of 4 trees selected at random from the validation dataset. 84% (CI: 79–88%) of the validation points fell within the 95% confidence interval of their estimated survival probability fitted with the model building dataset.

Table 6
Ranking of variables based on change in the size of Akaike Information Criterion (AIC) value without the variable in question for the Cox PH regression model.

Ranking of variables in order of importance	AIC value without the variable in question
Strata latitude–longitude and initial year	91239.780
logDBH	67948.624
PBAH/TPH quadratic polynomial[a]	67070.601
SIM cubic polynomial[b]	66991.253
BAINLDH cubic polynomial[b]	66975.530
PAIDBH	66947.246
StAGE quadratic polynomial[a]	66927.458
AVGHT5	66917.127
Included variables	
Strata latitude–longitude and initial year only	69943.471
Full model (strata and all the covariates)	66907.125
Null model (No strata and no covariates)	95970.203

[a] Includes 1st and 2nd degrees terms.
[b] Includes 1st, 2nd, and 3rd degrees terms.

(DBH) and DBH periodic annual increment (PAIDBH). While the probability of survival decreased with increasing average of the 5 tallest trees in the plot (AVGHT5) when other selected covariates were included in the models.

The relative importance of a variable in a model is assessed by the change in the size of the Akaike Information Criterion (AIC) without the variable (or polynomial function of the variable) in question in the model (Uzoh and Oliver, 2008). Table 6 shows the ranking of the variables based on this criterion for the Cox Proportional Hazard model. Table 7 shows the ranking of variables for the logistic model. Both tables show that location as a function of latitude and longitude was the most important factor for tree survival.

We stratified the data into location using latitude, longitude, and initial year to account for spatial effects and autocorrelation. The latitude–longitude and initial year strata had the most significant effect in the Cox PH model (Table 6). The latitude–longitude two dimensional spatial smoothing had a greater effect on the probability of a tree surviving the next 5 years than any other variable for the logistic model (Tables 7). Latitude is an important variable because more northerly locations tend to be cooler, with shorter growing seasons, than more southerly locations. Because diameter growth is sensitive to length of growing season, mortality seems to increase with increasing latitude (Fig. 2). However, longitude had a different effect on tree survival. Mortality tended to decrease toward the east (Fig. 2). Plots located in the southwest are influenced by the summer monsoons, with peak precipitations in winter and summer months (Knapp et al., 2009) when plants need moisture the most. As one go eastward into Montana and South Dakota, summer thunderstorms are accompanied by more rainfall (Knapp et al., 2009), thereby increasing tree growth and decreasing mortality (Fig. 2).

Table 7
Ranking of variables based on change in the size of AIC value without the variable in question for the logistic model.

Ranking of variables in order of importance	AIC value without the variable in question
Spatial smoothing function	12198.830
StAGE cubic polynomial[b]	9117.2880
AVGHT5	7515.6170
logDBH	6950.8820
BAINLDH cubic polynomial[b]	6894.4340
PAIDBH	6861.5260
SLSINASP	6841.8470
SDI cubic polynomial[b]	6827.3500
PBAH/TPH cubic polynomial[b]	6824.7610
SLCOSASP	6758.6770
Included variables	
Spatial smoothing function only	14407.7900
Full model (spatial function and all the covariates)	6750.2990
Null model (no spatial function and no covariates)	20221.99

[b] Includes 1st, 2nd, and 3rd degrees terms.

The natural logarithm of DBH had the second largest effect on the probability of a tree surviving longer than a given time period. Further, DBH periodic annual increment (PAIDBH) had the sixth greatest effect (Table 6). For the logistic model (Table 7), the natural logarithm of DBH and PAIDBH had the 4th and 6th greatest effect on the probability of a tree surviving the next 5 years. In both analyses, the models showed that the probability of survival increased with increasing diameter at breast height (DBH) and DBH periodic annual increment (PAIDBH) (depicted graphically in Fig. 4). The magnitude of DBH and its rate of increase is an indication of tree vigor (Wyckoff, 1990; Uzoh and Oliver, 2008). As a result, the probability of survival increased with increasing diameter at breast height (DBH) and DBH periodic annual increment (PAIDBH). This suggests that the less vigorous trees have relatively low survival probability (Barnes et al., 1998).

The quadratic polynomial of PBAH/TPH had the third greatest effect on the probability of a tree surviving longer than a given time period than any other variable (Table 6). For the logistic model, the quadratic polynomial of PBAH/TPH had the ninth greatest effect (Table 7). Within the fundamental constraint of site quality, number of trees per hectare significantly influences diameter growth (Wyckoff, 1990). In both analyses, the models showed that the probability of survival decreased with increasing average of the 5 tallest trees in the plot (AVGHT5) when other selected covariates were included in the models. For the Logistic model, the probability of survival increased with increasing plot basal area/number of trees per hectare (PBAH/TPH), increasing faster after PBAH/TPH ≈ 0.07 (Table 4, Fig. 3). For the Cox model, the function of PBAH/TPH was a quadratic polynomial, the maximum of this polynomial was obtained at PBAH/TPH = $[135.63/(2 * 973.45)] = 0.0696$, Table 5), and since the variable PBAH/TPH ranged from 0 to 0.12, trees with PBAH/TPH values ranging from 0 to about 0.07 units are at more risk than those greater than 0.07 units. In both models, for PBAH/TPH values greater than 0.07 the probability of survival increased with increasing PBAH/TPH. This confirms the findings of Oliver and Uzoh, 1997; Wunder et al., 2007.

The cubic polynomial of SIM (site index in meters) had the fourth largest effect on the probability of a tree surviving longer than a given time period than any other variable (Table 6). SIM was not used in the logistic model because the Akaike Information Criterion (AIC) for the effect of AVGHT5, the average height of the 5 tallest trees in the plot was smaller (Table 7). We tested SIM and AVGHT5 separately in the logistic model, and AVGHT5 out performed SIM. We believe also that the 15 smoothing function (LAT,LONG) might have reduced the effect of SIM in the logistic model; whereas in the Cox PH model, we used latitude–longitude and initial year strata. As a result, both SIM and AVGHT5 were both significant in the Cox PH model but not in the logistic model. However, from a forest management perspective, site index is still used as the primary indicator of site productive potential because site index is a numerical description of site productive potential rather than a generalized qualitative description (Husch, 1963). More importantly, SIM is an expression of the complex interplay between edaphic, climatic, and biotic factors of a site that determines tree growth potential measured by the volume of wood produced (Daniel et al., 1979; Spurr and Barnes, 1980). Additionally, the data were scattered over a vast geographic area of contrasting soils and climate, and included two varieties of ponderosa pine (*Pinus ponderosa* var. *ponderosa* and var. *scopulorum*), capturing the entire ecological amplitude of the species. Some of the genetic differences may also have affected diameter increment. Nevertheless, what we called SIM seemed to perform credibly in integrating and explaining these complex differences (Uzoh and Oliver, 2008). A contributing reason for the good performance of site index in the Cox PH model may have been that stockability was not a problem (McArdle and Meyer, 1930). All data were from sites capable of the productivity estimated by Meyer (1938).

The cubic polynomial of BAINLDH, basal area per hectare in larger diameter had the fifth largest effect for both models (Tables 6 and 7). Within the fundamental constraint of site quality, tree position significantly influenced diameter growth. The increment attained by an individual tree is dependent on its competitive status relative to neighboring trees. BAINLDH is a competition modifier that would reduce diameter growth rates relative to a tree's competitive status (Wyckoff, 1990). Density is a cardinal variable of stand dynamic because BAINLDH is a reflection of the proportion of light intercepted by neighbors and relating this proportion to biomass growth (Zeide, 2002). Consequently, trees with higher competitive status have more availability of light, water, and nutrients for growth (Yang et al., 2003). Therefore, the largest diameter tree in a plot would have a BAINLDH value of zero, while the smallest diameter tree in the plot would have a BAINLDH value near that of the plot's total basal area. As BAINLDH decreases, the probability of a tree surviving increases. The more open-grown the tree, the less it is influenced by competitors because the measure of relative size is tied to stand density. As a result, dominance is less of a factor in sparsely stocked stands (Wyckoff, 1990). The partial residual graph (Fig. 3) shows that with increasing BAINLDH from 0 to about 20 the probability of survival increases, then from 20 to 60 it fluctuates down and up and then increases.

The quadratic polynomial of stand age (StAGE) had the seventh largest effect on the probability of a tree surviving longer than a given time period (Table 6). However, the cubic polynomial of StAGE had the second most effects in predicting the probability of a tree surviving the next 5 years (Table 7). In even-aged stands, stand age is a complex measure of various physiological processes collectively known as aging (Zeide, 2001). This complex measure is best captured by stand closure. Closure changes with age, because lateral growth (crown and root) increases closure and mortality diminishes it (Zeide, 1991). As a result, closure decreases between 6 and 20 years when height increment reaches its maximum (Zeide, 1991). However, as stands mature, they become less shade tolerance and the gap created by mortality increases and the more effort they will need to supply foliage with the same amount of sap (Zeide, 2001). In an attempt to capture this complex physiological process, the cubic and the quadratic polynomials of stand age (StAGE) were used respectively in both models.

Table A1
Summary of the original dataset by latitude–longitude neighborhood and initial sampling year for Ponderosa Pine used to develop both models.

Province	Locale	Latitude	Longitude	Initial DBH	Total plots	Total trees	Total dead	Total alive	% Alive
1	11	41.32	121.983	37.07	3	287	79	208	77.57
1	12	41.33	121.93	44.8	3	172	36	136	81.07
1	15	37.05	119.23	24.33	3	32	1	31	96.97
1	16	39.77	122.65	27.5	2	32	0	32	100
1	17	41.33	122.32	12.55	4	66	0	66	100
1	18	37.07	119.22	13.67	3	34	0	34	100
1	19	39.7	121.23	9.85	2	27	0	27	100
1	20	39.1	120.75	13.73	3	51	0	51	100
1	21	39.08	120.73	13.23	3	57	0	57	100
1	22	41.3	121.9	7.32	6	120	1	119	99.28
1	23	40.52	121.62	12.8	4	72	0	72	100
1	24	37	119.15	17.43	4	47	0	47	100
1	25	38.57	120.17	48.8	2	19	1	18	95
1	26	37.05	119.23	16.63	3	38	0	38	100
1	652	39.28	122.67	3.09	15	689	23	666	96.65
1	653	39.47	121.22	2.06	10	120	2	118	98.34
1	1652	39.33	120.75	20.75	15	2004	0	2004	100
1	2007	40.22	121.17	26	1	2	0	2	100
1	2012	40.25	121.33	12.5	1	161	0	161	100
1	2013	40.22	121.17	15.6	1	69	0	69	100
1	2014	40.2	121.18	10.5	1	50	0	50	100
1	2015	40.22	121.2	12.1	1	63	3	60	95.2
1	2018	40.83	120.33	23.6	1	105	37	68	64.8
1	2019	41.83	120.33	16	1	11	8	3	27.3
1	2022	41.53	121.15	13.7	1	67	2	65	97
1	2023	41.53	121.15	10.7	1	98	0	98	100
1	2024	41.53	121.15	10.1	1	63	1	62	98.4
1	2028	40.5	121.85	29	1	29	1	28	96.6
1	2029	40.5	121.85	19.9	1	58	2	56	96.6
1	2030	41.32	121.98	31.7	1	34	13	21	61.8
1	2033	41.3	121.28	23.8	1	45	8	37	82.2
2	1	41.35	120.93	12.9	1	16	2	14	87.5
2	2	41.67	120.97	18.6	1	42	1	41	97.6
2	3	40.8	121.27	20.5	1	42	2	40	95.2
2	4	40.65	121.38	20	1	5	1	4	80
2	4	40.67	121.37	23.1	1	5	0	5	100
2	4	40.67	121.38	15.75	2	35	0	35	100
2	4	40.7	121.35	17	1	7	3	4	57.1
2	4	40.72	121.37	23.4	1	1	0	1	100
2	4	40.73	121.37	24.1	1	6	0	6	100
2	4	40.73	121.38	19.8	1	19	1	18	94.7
2	4	40.75	121.35	25.6	1	8	0	8	100
2	4	40.75	121.38	35.6	1	3	2	1	33.3
2	4	40.77	121.38	24.7	1	14	0	14	100
2	4	40.78	121.37	19.3	1	23	0	23	100
2	4	40.78	121.38	9	1	34	1	33	97.1
2	4	40.78	121.4	23.8	1	11	0	11	100
2	4	40.8	121.35	24.3	1	2	0	2	100
2	4	40.8	121.37	16	1	1	0	1	100
2	4	40.82	121.4	22.3	1	18	0	18	100
2	5	41.65	121.7	22.33	3	50	1	49	97.93
2	5	41.65	121.72	15.15	4	87	3	84	96.35
2	6	41.83	120.3	19.87	6	1053	177	876	87.02
2	7	41.58	121.37	14.8	1	81	13	68	84
2	10	41.62	120.33	21.07	3	604	130	474	80.93
2	13	40.73	121.13	5.2	1	28	3	25	89.3
2	14	40.57	120.93	31.7	3	114	3	111	98.27
2	27	40.98	121.65	33.1	3	54	2	52	95.17
2	35	43.73	121.58	4.87	15	1116	28	1088	98.58
2	10045	48.5	120.27	10.96	13	1725	345	1380	91.97
2	10050	43.77	121.72	25.31	18	1605	809	796	49.2
2	10072	43.77	121.72	6.48	9	213	0	213	100
3	10060	44.56	118.48	17.49	18	2279	831	1448	58.52
3	10082	44.62	118.6	16.63	15	486	55	431	92.51
3	10600	47.02	114.02	9.4	11	3356	813	2543	82.8
3	10600	47.1	114.4	8.8	3	1130	213	917	84.37
4	10700	44.15	103.63	9.4	7	776	128	648	89.31
4	10700	44.15	103.65	9.68	10	896	98	798	90.92
4	10700	44.16	103.63	12.7	1	187	31	156	83.4
4	10700	44.17	103.62	9.8	1	117	8	109	93.2
4	10700	44.17	103.65	9.25	2	235	10	225	96.75
4	10800	44.15	103.63	17.65	6	737	45	692	94.93
4	10800	44.15	103.65	16.4	1	131	1	130	99.2
4	10800	44.16	103.65	14.1	1	202	29	173	85.6

Table A1 (*continued*)

Province	Locale	Latitude	Longitude	Initial DBH	Total plots	Total trees	Total dead	Total alive	% Alive
4	10800	44.17	103.6	16.8	1	97	1	96	99
4	10800	44.17	103.63	16	1	68	0	68	100
4	10800	44.17	103.65	16.39	9	1098	57	1041	95.19
4	10800	44.18	103.65	15.7	2	216	19	197	94.85
5	10900	35.28	111.72	12.61	18	5694	753	4941	87.06
			Total	17.93	305	29449	4837	24612	91.18

Table A2
Mortality data summary for 5-year measurement interval for Ponderosa Pine used to develop the logistic model.

Province	Locale	Latitude	Longitude	Total plots	Total trees	Total dead	Total alive	% Alive
1	11	41.32	121.983	1	9	9	0	0
1	15	37.05	119.23	3	32	1	31	97
1	16	39.77	122.65	2	32	0	32	100
1	17	41.33	122.32	4	66	0	66	100
1	18	37.07	119.22	3	34	0	34	100
1	20	39.1	120.75	3	51	0	51	100
1	21	39.08	120.73	3	57	0	57	100
1	22	41.3	121.9	6	120	1	119	99.33
1	23	40.52	121.62	4	72	0	72	100
1	24	37	119.15	4	47	0	47	100
1	25	38.57	120.17	2	19	1	18	95
1	26	37.05	119.23	3	38	0	38	100
1	652	39.28	122.67	9	20	20	0	0
1	1652	39.33	120.75	15	1955	0	1955	100
1	2007	40.22	121.17	1	2	0	2	100
1	2012	40.25	121.33	1	161	0	161	100
1	2018	40.83	120.33	1	105	37	68	65
1	2019	41.83	120.33	1	4	4	0	0
1	2022	41.53	121.15	1	67	2	65	97
1	2023	41.53	121.15	1	24	0	24	100
1	2024	41.53	121.15	1	11	0	11	100
2	1	41.35	120.93	1	16	2	14	88
2	2	41.67	120.97	1	42	1	41	98
2	5	41.65	121.7	3	50	1	49	98
2	5	41.65	121.72	4	87	3	84	96.25
2	6	41.83	120.3	5	752	177	575	84.4
2	7	41.58	121.37	1	75	7	68	91
2	10	41.62	120.33	3	471	71	400	87
2	14	40.57	120.93	3	114	3	111	98.33
2	27	40.98	121.65	3	53	1	52	98
2	35	43.73	121.58	15	1097	13	1084	99.47
2	10045	48.5	120.27	13	1644	264	1380	93.23
2	10050	43.77	121.72	18	805	805	0	0
2	10072	43.77	121.72	9	210	0	210	100
3	10060	44.56	118.48	18	703	703	0	0
3	10082	44.62	118.6	6	33	33	0	0
3	10600	47.02	114.02	11	3355	813	2542	82.55
3	10600	47.1	114.4	3	1072	156	916	88
4	10700	44.15	103.63	6	149	32	117	80.5
4	10700	44.15	103.65	9	211	34	177	81
4	10700	44.17	103.62	1	28	8	20	71
4	10700	44.17	103.65	2	57	10	47	85.5
4	10800	44.15	103.63	5	168	33	135	84.8
4	10800	44.15	103.65	1	29	1	28	97
4	10800	44.17	103.6	1	25	1	24	96
4	10800	44.17	103.63	1	19	0	19	100
4	10800	44.17	103.65	9	220	57	163	79.56
4	10800	44.18	103.65	1	13	0	13	100
5	10900	35.28	111.72	18	5694	753	4941	87.06
			Total	240	20118	4057	16061	82

AVGHT5, the average height of the 5 tallest trees in each plot had the third largest effect on the probability of a tree surviving the next 5 years (Table 7). However, AVGHT5 had the eighth largest effect on the probability of a tree surviving longer than a given time period (Table 6) because of the effect of site index (SIM). In this study, different methods were used at different locations for sampling tree height. At some locations, every tree height in each plot was measured; at others, a systematic sample of tree heights were measured; yet at other locations, height sample trees were randomly selected within 2 in. diameter classes across the range of tree sizes. Height measurements were repeated on the same trees (Uzoh and Oliver, 2006). AVGHT5 was calculated from the 5 tallest trees in each plot. The methods used in sampling tree heights notwithstanding, in this context, AVGHT5 can be viewed as an expression of site productive potential like SIM. Because, SIM which is used as an indicator of site quality is the average height attainable by the dominant trees of a species at a specified forest stand at a chosen reference age (Spur, 1952; Spurr and Barnes, 1980; Nigh 1996, 1997; Chen et al., 1998). In both analyses, the models showed that the probability of survival decreased with increasing AVGHT5.

The cubic polynomial of SDI had the eight largest effects on the probability of a tree surviving the next 5 years (Table 7). The importance of SDI in the model suggests that the growth and mortality of all trees in a stand is affected by stand density—trees with the largest diameters as well as those with the smallest diameters. This relationship is in accordance with that reported for the two levels-of-growing-stock installations in Oregon (Cochran and Barrett, 1995, 1999). Also, this confirms the findings of Hann and Hanus on diameter growth (2002).

Stage's (1976) transformation of slope (SL) and aspect (ASP) (*SL*[cos(*ASP*)]) had the tenth largest effect on the probability of a tree surviving the next 5 years (Table 7). The transformation of slope and aspect has two important properties, it is circular, and optima exist with respect to both slope and aspect (Fig. 6). Factors such as slope, aspect, latitude, and longitude generally have no direct effect on tree growth, but act indirectly by influencing moisture, temperature, light, and other chemical and physical agents of the site (Uzoh, 2001).

The models developed in this analysis appear to perform well. The models are enhanced by confining the data set to permanent plots in pure, even-aged stands of ponderosa pine and by following the growth of individually tagged trees for long time periods. Sixty-eight percent of the plots that we used were followed for 20 years or longer. The diverse ecological requirements of ponderosa pine trees represented in the data base should enhance model performance and would encourage use of the models throughout the range of ponderosa pine in the United States.

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Appendix A

See Tables A1 and A2.

Appendix B

Predicting survival for the next 5 years using statistical package R

Two pieces of information are needed:

1. Data sets.
   a) The 33 estimated logistic coefficients in data set: **logistic_coeff.txt**.
   b) The 33x33 covariance matrix of the coefficients: **logistic_var.matrix.txt**.
   c) 17X42 matrix with the nodes information about latitude, longitude (42 locations) and 15 nodes resulting from the smoothing process: **nodes.txt**.
   d) New data. Values of the covariates for the new prediction: LAT, LONG, logDBH, SLSINASP, SLCOSASP, PBAHTPH, AVGDHT5, StAGE, BAINLDH, and SDI in metric units.
2. R source with the procedure steps.
   a. Read the first 3 files.
   b. Enter the new covariate values.
   c. Calculate the cubic orthogonal polynomials.
   d. Create new R data set.
   e. Calculate the predicted probability of surviving for the next 5 years (and 95% confidence intervals) from the new data.
   f. Print results.

The needed data sets are shown after the R procedure. They should be extracted and saved as .txt files.

R procedure

```
##################################### a #####################################

#Read the first 3 data files
coeff=read.delim("My Directory\\logistic_coeff.txt")
var.matrix=read.delim("My Directory\\logistic_var.matrix.txt")
nodes=read.delim("My Directory\\logistic_nodes.txt")

##################################### b #####################################
#Enter new data.  Here you enter your new information
#Example 1:
```

```
lat= 41.32
long= -121.983
#Covariates in metric units
DBH=24.13
logDBH=3.18345588
PAIDBH=0.4410189
SLSINASP=0                    #Slope=0
SLCOSASP=0
PBAHTPH=0.08659498                  # PBAHTPH = PBAH/TPH
StAGE=53
BAINLDH=32.18324
SDI=644.2743
AVGDHT5=37.33817
################################## c ########################################
#Calculate the cubic orthogonal polynomials for StAge
tt=StAGE
poly1age=-0.02219166 +0.0003681416*tt
poly2age=3.645953e-02+(-1.475448e-03)*tt+(1.311867e-05)*(tt**2)
poly3age=-6.502978e-02+(4.563075e-03)*tt+(-8.734801e-05)*(tt**2)+(4.936269e-07)*(tt**3)
#Calculate the cubic orthogonal polynomials for BAINLDH
tt=BAINLDH
poly1bai=-0.0118490809 +0.0005710529*tt
poly2bai=1.335654e-02+(-1.534155e-03)*tt+(3.169364e-05 )*(tt**2)
poly3bai=-1.541688e-02+(3.090818e-03)*tt+(-1.342207e-04)*(tt**2)+(1.516353e-06)*(tt**3)
# Calculate the cubic orthogonal polynomials for PBAHTPH           (PBAHTPH = PBAH/TPH)
tt=PBAHTPH
poly1bath=-0.007600637  +0.51566385*tt
poly2bath= 0.008832939 +(-1.132568629)*tt+(19.4479883845)*(tt**2)
poly3bath=-0.01030015+(1.9919751)*tt+(-73.06411045)*(tt**2)+(621.64906300)*(tt**3)
# Calculate the cubic orthogonal polynomials for SDI
tt=SDI
poly1sdi=-1.515008e-02  +(2.518403e-05)*tt
poly2sdi=  2.500387e-02 +(-9.103388e-05)*tt+(6.759525e-08)*(tt**2)
poly3sdi=-3.951856e-02+(2.450324e-04)*tt+(-4.040836e-07)*(tt**2)+(1.890306e-10 )*(tt**3)
################################# d ##########################################
#Create new R data set
newd=data.frame(int=1,logDBH1=logDBH,PAIDBH1=PAIDBH,SLSINASP1=SLSINASP,SLCOSASP1=SLCOSASP,
   PBAHTPH=poly1bath,PBAHTPHsq=poly2bath,PBAHTPHcu=poly3bath,
   StAGE=poly1age,StAGEsq=poly2age,StAGEcu=poly3age,
   BAINLDH=poly1bai,BAINLDHsq=poly2bai,BAINLDHcu=poly3bai,
   SDI=poly1sdi,SDIsq=poly2sdi,SDIcu=poly3sdi,
   AVGDHT=AVGDHT5)
newd                                         #Print newd
#Get row number for the given lat and long on the nodes matrix
nn=nodes[,1:2]
for (i in 1:42){
if(nodes[i,1]==lat & nodes[i,2]==long) {rn=i}}
rn                                                      #rn should be 18
DX=cbind(newd,nodes[rn,3:17])    #linear predictors
DX2=as.vector(t(DX))
coeff2=as.vector(coeff[,2])
################################# e #########################################
# Calculate the predicted probability for the new data
lpred=t(DX2) %*% coeff2
var.matrix2=as.matrix(var.matrix[,2:34])
var.sum=t(DX2) %*% var.matrix2 %*% DX2
se=var.sum**.5
lb=lpred-1.96*se
ub=lpred+1.96*se
 predicted=exp(lpred)/(1+exp(lpred))
 predlb=exp(lb)/(1+exp(lb))
 predub=exp(ub)/(1+exp(ub))
################################# e #########################################
#Print results
predicted
predlb
predub
##############Results should be: ##################################################
#predicted = 0.08684974
#pred95%LB = 0.01454718
#pred95%UB = 0.3799553
#There is of 8.7% (within an 95% confidence interval of 1.5%  to 38%)  probability of surviving the next 5 years .
#####################################################################################
```

```
#Example 2

lat= 43.73
long= -121.58
#Covariates in metric units
DBH=7.389
logDBH=2
PAIDBH=0.45
SLSINASP=0                #Slope=0
SLCOSASP=0
PBAHTPH=0.006             # PBAHTPH = PBAH/TPH
StAGE=80
BAINLDH=34
SDI=800
AVGDHT5=20
#Calculate the cubic orthogonal polynomials for StAge
tt=StAGE
poly1age=-0.02219166 +0.0003681416*tt
poly2age=3.645953e-02+(-1.475448e-03)*tt+(1.311867e-05)*(tt**2)
poly3age=-6.502978e-02+(4.563075e-03)*tt+(-8.734801e-05)*(tt**2)+(4.936269e-07)*(tt**3)
#Calculate the cubic orthogonal polynomials for BAINLDH
tt=BAINLDH
poly1bai=-0.0118490809 +0.0005710529*tt
poly2bai=1.335654e-02+(-1.534155e-03)*tt+(3.169364e-05 )*(tt**2)
poly3bai=-1.541688e-02+(3.090818e-03)*tt+(-1.342207e-04)*(tt**2)+(1.516353e-06)*(tt**3)
# Calculate the cubic orthogonal polynomials for PBAHTPH          (PBAHTPH = PBAH/TPH)
tt=PBAHTPH
poly1bath=-0.007600637  +0.51566385*tt
poly2bath= 0.008832939 +(-1.132568629)*tt+(19.4479883845)*(tt**2)
poly3bath=-0.01030015+(1.9919751)*tt+(-73.06411045)*(tt**2)+(621.64906300)*(tt**3)
# Calculate the cubic orthogonal polynomials for SDI
tt=SDI
poly1sdi=-1.515008e-02  +(2.518403e-05)*tt
poly2sdi=  2.500387e-02 +(-9.103388e-05)*tt+(6.759525e-08)*(tt**2)
poly3sdi=-3.951856e-02+(2.450324e-04)*tt+(-4.040836e-07)*(tt**2)+(1.890306e-10 )*(tt**3)
#Create new R data set
newd=data.frame(int=1,logDBH1=logDBH,PAIDBH1=PAIDBH,SLSINASP1=SLSINASP,SLCOSASP1=SLCOSASP,
   PBAHTPH=poly1bath,PBAHTPHsq=poly2bath,PBAHTPHcu=poly3bath,
   StAGE=poly1age,StAGEsq=poly2age,StAGEcu=poly3age,
   BAINLDH=poly1bai,BAINLDHsq=poly2bai,BAINLDHcu=poly3bai,
   SDI=poly1sdi,SDIsq=poly2sdi,SDIcu=poly3sdi,
   AVGDHT=AVGDHT5)
newd                              #Print newd
#Get row number for the given lat and long on the nodes matrix
nn=nodes[,1:2]
for (i in 1:42){
if(nodes[i,1]==lat & nodes[i,2]==long) {rn=i}}
rn                                                    #rn should be 29
DX=cbind(newd,nodes[rn,3:17])    #linear predictors
DX2=as.vector(t(DX))
coeff2=as.vector(coeff[,2])
# Calculate the predicted probability for the new data
lpred=t(DX2) %*% coeff2
var.matrix2=as.matrix(var.matrix[,2:34])
var.sum=t(DX2) %*% var.matrix2 %*% DX2
se=var.sum**.5
lb=lpred-1.96*se
ub=lpred+1.96*se
 predicted=exp(lpred)/(1+exp(lpred))
 predlb=exp(lb)/(1+exp(lb))
 predub=exp(ub)/(1+exp(ub))
################################ e ########################################
#Print results
predicted
predlb
predub
##############Results should be: ##########################################################
#predicted = 0.5596293
#pred95%LB = 0.3938635
#pred95%UB = 0.7130854
#There is a 56% (within an 95% confidence interval of 39.3%  to 71.3%)  probability of surviving the next 5 years .
#########################################################################################
```

(a) Data: "**logistic_coeff.txt**" (33 coefficients):

(Intercept)	logDBH	PAIDBH	SLSINASP	SLCOSASP	PBAHTPH	PBAHTPHsq	PBAHTPHcu
7.237993	1.870987	3.674622	−0.24316	−0.03303	188.587	22.3473	116.7581

BAILNDH	BAILNDHsq	BAILNDHcu	SDI	SDIsq	SDIcu	StAGE	StAGEsq
59.31363	−65.0323	41.34843	−113.252	−51.3327	−16.6741	422.9727	260.1884

StAGEcu	AVGDHT5	node1	node2	node3	node4	node5	node6
−501.586	−0.57824	−19.0233	4.397767	−77.7858	−50.9232	54.70615	−31.1435

node7	node8	node9	node10	node11	node12	node13	node14	node15
−72.2762	53.98461	−26.9731	59.33849	80.84666	970.1026	239.2935	135.0102	56.41076

Data: logistic_var.matrix.txt (33X33 matrix).

Covariate	V1	V2	V3	V4	V5
(Intercept)	0.359704	−0.03467	−0.04075	−0.00187	0.00109
logDBH	−0.03467	0.017714	−0.00883	−0.00042	−0.00033
PAIDBH	−0.04075	−0.00883	0.130282	−9.66E−07	−7.93E−05
SLSINASP	−0.00187	−0.00042	−9.66E−07	0.00073	−8.39E−05
SLCOSASP	0.00109	−0.00033	−7.93E−05	−8.39E−05	8.99E−05
poly(PBAHTPH, 3)1	9.148419	−1.12823	−1.81009	−0.13497	0.026184
poly(PBAHTPH, 3)2	−2.06761	0.651784	0.125962	0.066587	−0.02203
poly(PBAHTPH, 3)3	4.783418	−0.24261	−0.46225	−0.04187	−0.01137
poly(StAGE, 3)1	4.7613	−0.01287	1.417948	−0.04595	0.048424
poly(StAGE, 3)2	0.978169	−0.1081	−1.40654	0.078121	−0.03805
poly(StAGE, 3)3	0.586042	0.257936	0.701784	0.02391	−0.00177
poly(BAINLDH, 3)1	−2.13999	0.817738	0.760424	−0.04682	−0.01745
poly(BAINLDH, 3)2	0.164821	−0.05742	−0.31273	0.026396	−0.00285
poly(BAINLDH, 3)3	0.247015	−0.08523	0.121639	−0.01211	0.000589
poly(SDI, 3)1	−0.48079	−0.74662	0.436677	0.138857	−0.0055
poly(SDI, 3)2	0.632942	−0.12518	−0.46876	0.221974	−0.02865
poly(SDI, 3)3	1.16882	−0.14485	0.063586	0.142682	−0.02128
AVGDHT5	−0.01055	−0.00045	0.000987	0.000209	−5.27E−06
te(LONG,LAT).1	0.060456	−0.00854	0.114707	0.009442	0.000558
te(LONG,LAT).2	−0.28823	0.005699	−0.10468	−0.01473	0.001175
te(LONG,LAT).3	0.948155	0.783974	−2.29707	−0.27341	0.006545
te(LONG,LAT).4	3.196382	−0.42786	1.638305	0.303841	−0.0216
te(LONG,LAT).5	−0.94465	0.075267	−0.51757	−0.07569	0.002188
te(LONG,LAT).6	0.481279	−0.03885	0.365466	0.042368	−0.00055
te(LONG,LAT).7	0.971884	0.172103	−0.19465	−0.01624	0.002319
te(LONG,LAT).8	−1.18148	0.191498	−1.25777	−0.07569	−0.00631
te(LONG,LAT).9	0.465015	−0.09001	0.562601	0.046587	0.001999
te(LONG,LAT).10	−1.25898	0.075977	−0.68479	−0.08343	0.00067
te(LONG,LAT).11	−1.22974	−0.00586	−0.43017	−0.07198	−0.00214
te(LONG,LAT).12	−0.29565	−2.92761	4.697684	0.572678	−0.08023
te(LONG,LAT).13	−1.80464	−0.37076	1.051458	0.306242	0.012388
te(LONG,LAT).14	−0.52064	−0.1192	0.232656	0.155526	−0.00485
te(LONG,LAT).15	−8.33025	−0.34425	1.037869	−0.15456	0.11402

V6	V7	V8	V9	V10	V11	V12
9.148419	−2.06761	4.783418	4.7613	0.978169	0.586042	−2.13999
−1.12823	0.651784	−0.24261	−0.01287	−0.1081	0.257936	0.817738
−1.81009	0.125962	−0.46225	1.417948	−1.40654	0.701784	0.760424
−0.13497	0.066587	−0.04187	−0.04595	0.078121	0.02391	−0.04682
0.026184	−0.02203	−0.01137	0.048424	−0.03805	−0.00177	−0.01745
521.5808	−80.679	176.2101	−18.5853	117.9782	−16.4996	−85.9347
−80.679	214.7875	54.83995	33.46968	−6.82583	15.00553	37.60692
176.2101	54.83995	198.6208	31.09717	22.41352	55.81088	−19.1717
−18.5853	33.46968	31.09717	348.9891	−90.6585	−33.434	11.39823
117.9782	−6.82583	22.41352	−90.6585	210.0909	−187.399	−28.6689
−16.4996	15.00553	55.81088	−33.434	−187.399	428.8838	22.1994
−85.9347	37.60692	−19.1717	11.39823	−28.6689	22.1994	94.50038
9.272555	0.490857	4.1876	−7.17567	2.767675	10.05249	−13.2331
13.58127	−6.17344	−1.28312	3.267666	7.187565	−4.4944	−0.73821
76.92396	−36.3845	−13.9731	−91.1843	70.53958	−39.2073	−77.9591
−10.7079	19.17115	12.4379	−2.30649	28.80425	26.30294	−10.8631
−24.8412	11.52049	12.48645	29.11628	−7.02308	46.59593	−14.9737
−0.28804	0.025195	−0.18181	−0.20385	−0.0098	−0.08077	−0.01838
−7.61687	0.054353	−1.10667	9.000413	−11.1263	12.95628	0.3298
−1.24731	−9.51373	−7.91913	−11.8754	4.045229	−3.52796	−0.0739
90.03967	34.41563	68.57627	−84.1213	1.41637	86.82466	35.25412
−22.0783	26.50879	39.90948	126.4546	−57.9997	124.8498	−24.2185
15.62917	−11.742	−9.76151	−52.2811	32.05068	−40.0768	2.565903
−18.6082	9.131046	2.86994	36.49978	−23.1841	17.64785	0.00504
3.531903	19.15929	25.05983	21.44794	−32.7157	61.78883	10.19268
21.08959	−10.9979	−8.65683	−95.915	61.25264	−50.2458	4.852536
−14.0013	6.451937	1.447349	45.70874	−27.287	23.7194	−2.30554
25.36937	−18.1957	−11.8277	−74.0732	44.83207	−39.195	1.116257
29.79265	−19.8135	−13.5009	−66.3276	48.92383	−58.9241	−3.83416
375.676	−185.338	47.5225	−241.202	300.4678	45.25816	−201.122
69.76734	−36.6503	20.17939	−75.2119	56.50363	72.88117	−20.6404
48.45427	−19.5239	16.18642	−47.0408	49.31318	24.85006	−11.4601
−37.1101	−46.7367	−82.5065	−161.007	−60.1339	19.75113	20.03228

V13	V14	V15	V16	V17	V18	V19
0.164821	0.247015	−0.48079	0.632942	1.16882	−0.01055	0.060456
−0.05742	−0.08523	−0.74662	−0.12518	−0.14485	−0.00045	−0.00854
−0.31273	0.121639	0.436677	−0.46876	0.063586	0.000987	0.114707
0.026396	−0.01211	0.138857	0.221974	0.142682	0.000209	0.009442
−0.00285	0.000589	−0.0055	−0.02865	−0.02128	−5.27E−06	0.000558
9.272555	13.58127	76.92396	−10.7079	−24.8412	−0.28804	−7.61687
0.490857	−6.17344	−36.3845	19.17115	11.52049	0.025195	0.054353
4.1876	−1.28312	−13.9731	12.4379	12.48645	−0.18181	−1.10667
−7.17567	3.267666	−91.1843	−2.30649	29.11628	−0.20385	9.000413
2.767675	7.187565	70.53958	28.80425	−7.02308	−0.0098	−11.1263
10.05249	−4.4944	−39.2073	26.30294	46.59593	−0.08077	12.95628
−13.2331	−0.73821	−77.9591	−10.8631	−14.9737	−0.01838	0.3298
38.08049	−4.06396	6.039766	−12.9973	3.392324	0.004103	0.311422
−4.06396	36.58586	8.901691	0.22584	−9.31762	−0.00607	0.641156
6.039766	8.901691	249.9275	12.38513	−28.0084	0.136161	−0.02264
−12.9973	0.22584	12.38513	119.3395	53.7419	0.01211	2.116917
3.392324	−9.31762	−28.0084	53.7419	88.99729	−0.03251	5.245609
0.004103	−0.00607	0.136161	0.01211	−0.03251	0.000553	0.000158
0.311422	0.641156	−0.02264	2.116917	5.245609	0.000158	4.715726
−0.22885	−0.03206	0.312705	−4.90929	−5.48596	0.006209	−6.36086
−4.43894	−25.2403	−51.2357	−69.4142	−95.706	−0.11068	−52.0831
11.05293	18.39232	43.67562	103.186	115.0134	−0.03876	63.08161
−2.62547	−3.04218	−7.59571	−22.0076	−29.7359	0.01235	−24.1648
0.693853	1.439266	−0.02518	11.37504	18.06461	−0.00355	16.12164

Appendix B (*continued*)

V13	V14	V15	V16	V17	V18	V19
0.126679	−4.98421	−20.0676	−0.7171	1.49142	−0.04142	6.031288
−3.43943	−7.26703	−1.70789	−14.9257	−42.0591	0.020443	−42.5603
1.699074	4.084204	2.381391	10.57451	21.62126	−0.0054	19.86098
−1.82987	−2.58683	−2.52738	−23.1099	−35.4165	0.016635	−32.7003
−1.52372	−0.28061	10.38773	−23.3046	−33.1907	0.023265	−26.4784
48.86775	118.9499	266.1741	233.8182	224.6592	0.030808	−27.8938
−11.9415	34.12328	−7.96987	128.7856	117.7737	0.004781	1.434136
−6.42304	16.00713	27.53853	63.59566	45.2414	−0.00241	−6.7884
−14.616	11.14877	−307.628	−16.7886	60.0582	0.104305	−16.6091

V20	V21	V22	V23	V24	V25	V26
−0.28823	0.948155	3.196382	−0.94465	0.481279	0.971884	−1.18148
0.005699	0.783974	−0.42786	0.075267	−0.03885	0.172103	0.191498
−0.10468	−2.29707	1.638305	−0.51757	0.365466	−0.19465	−1.25777
−0.01473	−0.27341	0.303841	−0.07569	0.042368	−0.01624	−0.07569
0.001175	0.006545	−0.0216	0.002188	−0.00055	0.002319	−0.00631
−1.24731	90.03967	−22.0783	15.62917	−18.6082	3.531903	21.08959
−9.51373	34.41563	26.50879	−11.742	9.131046	19.15929	−10.9979
−7.91913	68.57627	39.90948	−9.76151	2.86994	25.05983	−8.65683
−11.8754	−84.1213	126.4546	−52.2811	36.49978	21.44794	−95.915
4.045229	1.41637	−57.9997	32.05068	−23.1841	−32.7157	61.25264
−3.52796	86.82466	124.8498	−40.0768	17.64785	61.78883	−50.2458
−0.0739	35.25412	−24.2185	2.565903	0.00504	10.19268	4.852536
−0.22885	−4.43894	11.05293	−2.62547	0.693853	0.126679	−3.43943
−0.03206	−25.2403	18.39232	−3.04218	1.439266	−4.98421	−7.26703
0.312705	−51.2357	43.67562	−7.59571	−0.02518	−20.0676	−1.70789
−4.90929	−69.4142	103.186	−22.0076	11.37504	−0.7171	−14.9257
−5.48596	−95.706	115.0134	−29.7359	18.06461	1.49142	−42.0591
0.006209	−0.11068	−0.03876	0.01235	−0.00355	−0.04142	0.020443
−6.36086	−52.0831	63.08161	−24.1648	16.12164	6.031288	−42.5603
16.59989	82.11102	−114.275	45.88932	−31.4812	−15.5659	78.83991
82.11102	1167.343	−993.361	333.3953	−223.738	38.57231	617.7436
−114.275	−993.361	1194.822	−403.905	264.4516	63.02499	−703.634
45.88932	333.3953	−403.905	154.9508	−103.618	−37.6202	267.4911
−31.4812	−223.738	264.4516	−103.618	70.30856	25.42179	−179.822
−15.5659	38.57231	63.02499	−37.6202	25.42179	42.05532	−54.198
78.83991	617.7436	−703.634	267.4911	−179.822	−54.198	481.709
−35.4531	−292.926	328.4491	−123.614	82.59947	22.84957	−221.219
65.64884	443.9439	−541.348	212.5843	−144.077	−55.8822	367.1464
51.0321	327.7876	−426.746	168.742	−113.581	−51.8876	287.1544
137.415	−1091.49	726.9484	229.5244	−212.434	−502.518	179.4844
15.44433	−430.767	321.7467	5.776071	−16.7026	−104.644	−72.3292
21.26559	−70.1015	29.01179	47.20096	−39.0423	−52.0857	52.88542
43.45119	−262.472	−153.112	146.4991	−92.8903	−159.781	111.4768

V27	V28	V29	V30	V31	V32	V33
0.465015	−1.25898	−1.22974	−0.29565	−1.80464	−0.52064	−8.33025
−0.09001	0.075977	−0.00586	−2.92761	−0.37076	−0.1192	−0.34425
0.562601	−0.68479	−0.43017	4.697684	1.051458	0.232656	1.037869
0.046587	−0.08343	−0.07198	0.572678	0.306242	0.155526	−0.15456
0.001999	0.00067	−0.00214	−0.08023	0.012388	−0.00485	0.11402
−14.0013	25.36937	29.79265	375.676	69.76734	48.45427	−37.1101
6.451937	−18.1957	−19.8135	−185.338	−36.6503	−19.5239	−46.7367
1.447349	−11.8277	−13.5009	47.5225	20.17939	16.18642	−82.5065
45.70874	−74.0732	−66.3276	−241.202	−75.2119	−47.0408	−161.007

(*continued on next page*)

Appendix B (*continued*)

V27	V28	V29	V30	V31	V32	V33
−27.287	44.83207	48.92383	300.4678	56.50363	49.31318	−60.1339
23.7194	−39.195	−58.9241	45.25816	72.88117	24.85006	19.75113
−2.30554	1.116257	−3.83416	−201.122	−20.6404	−11.4601	20.03228
1.699074	−1.82987	−1.52372	48.86775	−11.9415	−6.42304	−14.616
4.084204	−2.58683	−0.28061	118.9499	34.12328	16.00713	11.14877
2.381391	−2.52738	10.38773	266.1741	−7.96987	27.53853	−307.628
10.57451	−23.1099	−23.3046	233.8182	128.7856	63.59566	−16.7886
21.62126	−35.4165	−33.1907	224.6592	117.7737	45.2414	60.0582
−0.0054	0.016635	0.023265	0.030808	0.004781	−0.00241	0.104305
19.86098	−32.7003	−26.4784	−27.8938	1.434136	−6.7884	−16.6091
−35.4531	65.64884	51.0321	137.415	15.44433	21.26559	43.45119
−292.926	443.9439	327.7876	−1091.49	−430.767	−70.1015	−262.472
328.4491	−541.348	−426.746	726.9484	321.7467	29.01179	−153.112
−123.614	212.5843	168.742	229.5244	5.776071	47.20096	146.4991
82.59947	−144.077	−113.581	−212.434	−16.7026	−39.0423	−92.8903
22.84957	−55.8822	−51.8876	−502.518	−104.644	−52.0857	−159.781
−221.219	367.1464	287.1544	179.4844	−72.3292	52.88542	111.4768
103.0333	−168.129	−131.937	−50.8825	53.26173	−14.1529	−44.8074
−168.129	296.3196	233.7351	466.2608	56.72355	90.04534	212.781
−131.937	233.7351	189.2344	433.5145	31.10491	61.25738	185.511
−50.8825	466.2608	433.5145	14564.45	3813.094	1729.465	3455.465
53.26173	56.72355	31.10491	3813.094	5864.716	3027.986	2273.498
−14.1529	90.04534	61.25738	1729.465	3027.986	1605.016	983.3813
−44.8074	212.781	185.511	3455.465	2273.498	983.3813	2924.639

Data: **nodes.txt (**17X42 matrix [Lat, Long] (42 locations) and 15 nodes: te.LONG.LAT).

LAT	LONG	te(LONG,LAT).1	te(LONG,LAT).2	te(LONG,LAT).3	te(LONG,LAT).4	te(LONG,LAT).5	te(LONG,LAT).6	te(LONG,LAT).7
35.28	−111.72	0.221186632	−0.296121369	−0.158164501	−1.015601166	−0.713399409	0.504848515	0.522162905
37	−119.15	0.002836633	0.008971955	0.009692381	−0.108400695	−0.017319608	0.00284612	−0.032046226
37.05	−119.23	−0.014092923	0.018867396	0.010077463	−0.07930339	0.045454298	−0.032166462	−0.033269649
37.07	−119.22	−0.012557179	0.018476225	0.010503609	−0.08656569	0.039438387	−0.029148334	−0.034682731
38.57	−120.17	−0.238257906	0.10868506	−0.004757642	0.170979045	1.024118434	−0.480935926	0.01710961
39.08	−120.73	−0.216189729	0.065925497	−0.020475372	0.272952758	1.363447538	−0.546526552	0.070991527
39.1	−120.75	−0.211839823	0.062946336	−0.020856965	0.274122943	1.368912425	−0.544450443	0.072333033
39.28	−122.67	1.462530946	−0.565690647	0.011306409	−0.032554793	0.01865942	−0.013204637	−0.013657506
39.33	−120.75	−0.206784821	0.052747609	−0.020821041	0.24451884	1.338480956	−0.483064699	0.071864567
39.77	−122.65	1.310030691	−0.372550267	0.00995423	−0.03986893	0.050014496	−0.02425833	−0.016988571
40.22	−121.17	−0.047252215	−0.024235713	−0.017916583	0.149952411	1.080572139	−0.08952035	0.060603943
40.25	−121.33	0.024075735	−0.032232235	−0.017215898	0.143467564	1.036159862	−0.068391461	0.058378545
40.52	−121.62	0.162349409	−0.01068643	−0.011407383	0.086189598	0.77760763	0.094939369	0.036499779
40.57	−120.93	−0.10112382	−0.035816997	−0.011635473	0.088617691	0.863077997	0.144524079	0.037654445
40.83	−120.33	−0.114163874	−0.064846891	−0.004590991	0.034615509	0.529335153	0.267444306	0.01438966
40.98	−121.65	0.104475125	0.071490856	−0.004052343	0.018666936	0.479580406	0.394676488	0.007000408
41.3	−121.9	0.100380228	0.252954173	0.00014559	−0.017348464	0.214593839	0.497265655	−0.008801354
41.32	−121.983	0.112161616	0.304905613	−0.000235851	−0.015712489	0.184108973	0.462428006	−0.007980907
41.33	−122.32	0.186173427	0.51068332	−0.003390687	0.001445656	0.090118947	0.254670137	−0.000137881
41.35	−120.93	−0.03701111	−0.093399786	0.003499312	−0.028144844	0.269467048	0.761184087	−0.014011408
41.53	−121.15	−0.017641868	−0.049735912	0.007663902	−0.061151687	0.137858903	0.904088913	−0.027109281
41.58	−121.37	−0.011047943	0.033755989	0.008677192	−0.069723548	0.099301612	0.903975097	−0.030196844
41.62	−120.33	−0.006045088	−0.168381938	0.000858241	−0.006199103	0.026166304	0.770364704	−0.002995925
41.65	−121.72	−0.010143553	0.235125637	0.008044875	−0.063641126	0.040725368	0.796300307	−0.026778352
41.65	−121.7	−0.010465293	0.222202348	0.008227233	−0.065062717	0.041603155	0.807910617	−0.02737592
41.67	−120.97	−0.011800091	−0.105443334	0.00930461	−0.073281297	0.031530838	1.002993813	−0.030538826
41.83	−120.33	0.019645125	−0.191902008	0.00139007	−0.01501506	−0.093464144	0.885150206	−0.003605337
41.83	−120.3	0.020353039	−0.191418028	0.000750391	−0.009973088	−0.094161376	0.868049677	−0.001547979
43.73	−121.58	−0.169214174	0.293425166	0.050594862	−0.22476059	−0.725811131	1.518002542	0.033927969
43.77	−121.72	−0.251028618	0.446524014	0.061504178	−0.198667232	−0.672066486	1.390220271	0.037578573
44.15	−103.65	0.01259758	−0.014643799	−0.011665576	0.09955552	−0.03803215	0.006477535	0.038070232

Appendix B (*continued*)

LAT	LONG	te(LONG,LAT).1	te(LONG,LAT).2	te(LONG,LAT).3	te(LONG,LAT).4	te(LONG,LAT).5	te(LONG,LAT).6	te(LONG,LAT).7
44.15	−103.63	0.013692797	−0.016998712	−0.011385789	0.094251936	−0.042604244	0.01788758	0.037323504
44.17	−103.65	0.012595997	−0.01465826	−0.011656707	0.099592305	−0.0380229	0.00651344	0.038035132
44.17	−103.63	0.013693605	−0.017009742	−0.011381725	0.0942839	−0.042604364	0.017913136	0.037306595
44.17	−103.62	0.014242416	−0.018185498	−0.011244233	0.091629667	−0.044895125	0.023613054	0.036942323
44.17	−103.6	0.015340046	−0.020537025	−0.010969247	0.086321172	−0.049476677	0.035012963	0.036213775
44.18	−103.65	0.012594976	−0.01466515	−0.011651964	0.099608486	−0.03801762	0.006531196	0.03801655
44.56	−118.48	−0.009612897	0.06580088	−0.060686804	0.75783462	0.104621334	−0.615602592	0.184529152
44.62	−118.6	0.003332838	0.039484588	−0.058703553	0.708654025	0.051802905	−0.492991909	0.179895463
47.02	−114.02	−0.113990314	0.215841826	0.260616197	1.164781739	0.531424533	−1.377567003	−1.036321902
47.1	−114.4	−0.09926963	0.190905586	0.265990713	1.11567521	0.471982431	−1.260072028	−1.053596935
48.5	−120.27	−0.002308788	0.003090971	−0.169583741	−0.012991963	0.007446599	−0.005269705	0.754480588

te(LONG,LAT).8	te(LONG,LAT).9	te(LONG,LAT).10	te(LONG,LAT).11	te(LONG,LAT).12	te(LONG,LAT).13	te(LONG, LAT).14	te(LONG, LAT).15
1.016834086	0.59692539	−1.058839611	−0.829392723	0.135320876	0.129350237	−0.218874109	−0.06696
0.649545222	1.007550187	−0.512202772	0.057443563	0.010898522	−0.007276595	0.012949249	0.00406
0.617566573	0.985928678	−0.496565698	0.059896732	0.011143795	−0.00824156	0.013945581	0.004267
0.619032294	0.999544161	−0.501579611	0.062152353	0.011633799	−0.008510039	0.014477694	0.004441
0.068962077	0.707151487	−0.350815813	−0.013306906	−0.004133815	−0.00059373	−0.003030139	−0.00143
−0.136971768	0.359644791	−0.24892132	−0.099185774	−0.02139156	0.013821847	−0.025783248	−0.00814
−0.14198859	0.348318499	−0.245544399	−0.101408357	−0.021834882	0.01422715	−0.026383957	−0.00831
0.034708808	−0.015612967	0.02769463	0.0216933	0.004574634	−0.003383239	0.005724793	0.001751
−0.148444078	0.343004425	−0.234643269	−0.102021432	−0.021896181	0.014337655	−0.02658373	−0.00835
0.043333376	−0.022234934	0.035430015	0.027128186	0.005723446	−0.004212225	0.007155782	0.002191
−0.149003721	0.110003577	−0.124579486	−0.093288273	−0.019689327	0.014244065	−0.024596515	−0.00754
−0.144442495	0.064974168	−0.115252634	−0.090277786	−0.019037574	0.014079522	−0.023824021	−0.00729
−0.094502977	0.004280915	−0.078223161	−0.059105232	−0.012471997	0.009508631	−0.015586309	−0.00478
−0.099519303	0.147076309	−0.067071379	−0.062048688	−0.013050262	0.00893597	−0.01641929	−0.005
−0.046712412	0.285481132	0.085782517	−0.028632932	−0.005738644	0.002834237	−0.007847049	−0.0022
−0.027157819	−0.0122633	−0.041102648	−0.017005575	−0.003628961	0.002865603	−0.004395263	−0.00139
0.014645182	−0.021766426	−0.025743201	0.009207059	0.001890243	−0.001285407	0.002645529	0.000723
0.01344455	−0.020084042	−0.026868315	0.008458936	0.001734646	−0.001178809	0.002451993	0.000663
−0.003239065	−0.007303091	−0.027065984	−0.001987472	−0.000450329	0.000398	−0.00038045	−0.00017
0.024212881	0.017521331	0.105980006	0.014999739	0.003267652	−0.002614511	0.003480544	0.001253
0.062863429	−0.023931141	0.089367162	0.039247081	0.008297782	−0.006168496	0.010095642	0.003177
0.073041224	−0.033319427	0.051013406	0.045656797	0.009625532	−0.007115271	0.01209981	0.003685
0.005885268	0.00825483	0.376453405	0.003534513	0.000806546	−0.000654458	−0.000979669	0.00031
0.067763246	−0.030727289	0.00667231	0.042356139	0.008930514	−0.006602875	0.011529241	0.003419
0.069277391	−0.031402782	0.008963432	0.043302411	0.009130095	−0.00675052	0.011770925	0.003496
0.078382438	−0.036282142	0.163222113	0.049005273	0.010327897	−0.007630947	0.012211878	0.003954
0.019279593	−0.057882406	0.443572444	0.013136413	0.002401607	−0.001514507	0.000717596	0.000912
0.013897104	−0.057470503	0.456761034	0.009816675	0.00168661	−0.000980386	−0.000223806	0.000638
0.25777988	−0.080759763	0.139869641	0.155996988	0.034076754	−0.025462826	0.043132635	0.013086
0.228231409	−0.057239653	0.097685321	0.135868145	0.030211685	−0.022680163	0.038433827	0.011619
−0.106178652	0.029161327	−0.051818058	−0.06283845	0.006538603	−0.995076854	1.761062402	0.196229
−0.100509769	0.034051538	−0.060456005	−0.060704982	0.007344365	−0.997517201	1.765335683	0.196899
−0.106217927	0.029149345	−0.051870095	−0.062813858	0.006566156	−0.996675655	1.759973406	0.19888
−0.100543881	0.034049093	−0.060495644	−0.060696819	0.007372691	−0.999119515	1.764245562	0.199554
−0.097706826	0.03649899	−0.064808459	−0.059638286	0.007775964	−1.000341451	1.766381652	0.199892
−0.092032684	0.041398808	−0.073434131	−0.057521209	0.008582513	−1.002785331	1.770653844	0.200566
−0.106235207	0.029142891	−0.05189491	−0.062799983	0.006579583	−0.997442987	1.759392486	0.20021
−0.790866217	−1.048510774	1.756172488	−0.153589117	−0.107893475	0.071752217	−0.121342412	−0.03931
−0.737845037	−1.014159209	1.688284168	−0.122696661	−0.100782072	0.068191432	−0.115385291	−0.03695
−1.240781683	−0.77523419	1.051188387	0.91033739	−0.165286332	0.031783549	−0.068384057	0.052229
−1.188064761	−0.722807516	0.974127589	0.968952943	−0.158438809	0.041533608	−0.082645764	0.043313
0.013851587	−0.006230821	0.01105237	0.422084649	0.001825644	−0.001350182	0.00228465	−0.00142

References

Allison, Paul D., 2010. Survival Analysis Using SAS®: A Practical Guide, second ed. SAS Institute Inc., Gary, NC.

Barnes, B.V., Zak, D.R., Denton, S.R., Spurr, S.H., 1998. Forest Ecology, fourth ed. John Wiley & Sons, Inc., New York.

Boldt, C.E., Van Deusen, J.L., 1974. Silviculture of ponderosa pine in the Black Hills: the status of our knowledge. USDA For. Serv. Res. Pap. RM-124. 45 p.

Bröcker, J., Smith, L.A., 2007. Increasing the Reliability of Reliability Diagrams Weather and Forecasting 22(3).

Burnham, K.P., Anderson, D.R., 2002. Model Selection and Inference: A Practical Information-Theoretic Approach, second ed. Springer, New York.

Chen, H.Y.H., Klinka, K., Kabzems, R.D., 1998. Site index, site quality, and foliar nutrients of trembling aspen: relationships and predictions. Can. J. For. Res. 28, 1743–1755.

Clutter, J.L., Fortson, J.C., Pienaar, L.V., Brister, G.H., Bailey, R.L., 1983. Timber Management: A Quantitative Approach. John Wiley & Sons, New York.

Cochran, P.H., Barrett, J.W., 1995. Growth and Mortality of Ponderosa Pine Poles Thinned to Various Densities in the Blue Mountains of Oregon. U.S. For. Ser. Res. Pap. PNW-RP-483.

Cochran, P.H., Barrett, J.W., 1999. Growth of Ponderosa Pine Thinned to Different Stocking Levels in central Oregon: 30-year Results. U.S. For. Ser. Res. Pap. PNW-RP-508.

Cox, D.R., 1972. Regression Models and Life Tables. J. Roy. Stat. Soc., Ser. B 20, 187–220.

Cox, D.R., 1975. Partial likelihood. Biometrika 62, 269–276.

Daniel, T.W., Helms, J.A., Baker, F.S., 1979. Principles of Silviculture, second ed. McGraw-Hill, New York.

Ek, A.R., 1974. Nonlinear models for stand table projection in northern hardwood stand. Can. J. For. Res. 4, 23–27.

Fielding, A.H., Bell, J.F., 1997. A review of methods for the assessment of predictionerrors in conservation presence/absence models. Environ. Conserv. 24, 38–49.

Hamilton, D.A., Jr. 1974. Event Probability Estimated by Regression. USDA Forest Service Res. Pap. INT-152.

Hamilton Jr., D.A., 1986. A logistic model of mortality in thinned and unthinned mixed conifer stands of northern Idaho. For. Sci. 32, 989–1000.

Hann, D.W., Hanus, M.L., 2002. Enhanced diameter-growth-rate equations for undamaged and damaged trees in southwest Oregon. Res. Cont. 39. Oregon State University Forest Res. Lab. 54.

Hann, D.W., Wang, C.H., 1990. Mortality Equation for Individual Trees in the Mixed-conifer Zone of Southwest Oregon. Forest Research Laboratory, Oregon State University, Corvallis, Research Bulletin 67, 17 p.

Harms, W.R., 1983. An empirical function for predicting survival over a wide range of densities. In: Proceedings Second Biennial South Silvicultural Research Conference, 4–5 November 1982, Atlanta, GA. USDA Forest Service Gen. Tech. Rep. SE-24, pp. 334–337.

Hastie, Trevor, Tibshirani, Robert, 1990. Generalized Additive Models. Chapman and Hall, London.

Hastie, T., Tibshirani, R., Friedman, J., 2001. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer, New York.

Holmes, W.M., 1983. Confidence building in simulation models as a practical process. In: Proceedings of the 1983 Summer Computer Simulation Conference, 11–13 July 1983, Vancouver, BC. The Society for Modeling and Simulation International, San Diego, California, USA.

Hosmer, D.W., Lemeshow, S., 2000. Applied Logistic Regression, second ed. Wiley, New York, NY, US.

Husch, B., 1963. Forest Mensuration and Statistics. Ronald, New York.

Kleinbaum, D.G., Klein, M., 2005. Survival Analysis—A Self-Learning Text, second ed. Springer-Verlag, New York, p. 590.

Knapp, E.E., Estes, B.L., Kinner, C.N., 2009. Ecological Effects of Prescribed Fire Season: A Literature Review and Synthesis for Managers. Gen. Tech. Rep. PSW-GTR-224. U.S. Department of Agriculture, Forest Service, Pacific Southwest Research Station, Albany, CA, p. 80.

Kozak, A., Kozak, R., 2003. Does cross validation provide additional information in the evaluation of regression models? Can. J. For. Res. 33, 976–987.

Lee, Y.J., 1971. Predicting mortality for even-ages stands of lodgepole pine. For. Chron. 47, 29–32.

Lee, T.E., Wang, J.W., 2003. Statistical Methods for Survival Analysis. John Wiley and Sons, New Jersey.

Mayer, D.G., Stuart, M.A., Swain, A.J., 1994. Regression of real-world data on model output: an appropriate overall test of validity. Agric. Syst. 45, 93–104.

McArdle, R.E., Meyer, W.H., 1930. The Yield of Douglas-fir in the Pacific Northwest. USDA Tech. Bull. 201, 64 p.

McCullagh, Peter, Nelder, John A., 1991. Generalized Linear Models. Chapman & Hall, New York.

Meyer, W.H., 1938. Yield of Even-aged Stands of Ponderosa Pine. U.S. Tech. Bull. 630.

Monserud, A.R., 1976. Simulation of forest tree mortality. For. Sci. 22, 438–444.

Morehead, L.A., 1996. Determining the Factors Influential in the Validation of Computer-based Problem Solving Systems. Ph.D. Dissertation, Portland State University, Portland, Oregon, USA (University Microfilms UMI No. 9628864).

Moser, J.W., 1972. Dynamics of an uneven-aged forest stand. For. Sci. 18, 184–191.

Myers, C.A., 1967. Growing Stock Levels in Even-aged Ponderosa Pine. U.S. For. Ser. Res. Pap. RM-33.

Nigh, G.D., 1996. Growth intercept models for species without distinct annual branch whorls: western hemlock. Can. J. For. Res. 26, 1407–1415.

Nigh, G.D., 1997. A Sitka spruce height–age model with improved extrapolation properties. For. Chron. 73, 363–369.

Oliver, W.W., 1984. Brush Reduces Growth of Thinned Ponderosa Pine in Northern California. U.S. For. Ser. Res. Pap. PSW-172.

Oliver, W.W., 1997. Twenty-five-year growth and mortality of planted ponderosa pine repeatedly thinned to different stand densities in northern California. West. J. Appl. For. 12 (4), 122–130.

Oliver, W.W., Edminster, C.B., 1988. Growth of ponderosa pine thinned to different stocking levels in the western United States. In: Proceedings—Future Forests of the Mountain West. September 29–October 3, 1986, Missoula, Montana. Compiler by Schmidt, W.C. U.S. For. Ser. Gen. Tech. Rep. INT-243, pp. 153–159.

Oliver, W.W., Ryker, R.A., 1990. *Pinus Ponderosa* Dougl. Ex Laws. Ponderosa Pine. In: Burns, R.M., Honkala, B.H. (Technical Coordinators), Silvics of North America, Volume 1, Conifers. U.S. Agric. Hand Book, vol. 654, pp. 413–424.

Oliver, W.W., Uzoh, F.C.C., 1997. Maximum Stand Densities for Ponderosa Pine and Red and White Fir in Northern California. In: Proc. 18th Annual Forest Vegetation Management Conference, January 14–16, 1997, Sacramento. California Forest Veg. Manage. Conf., Redding, CA.

Pearce, J., Ferrier, S., 2000. Evaluating the predictive performance of habitat models developed using logistic regression. Ecol. Model. 133, 225–245.

Popper, K.R., 1963. Conjectures and Refutations. Routledge and Kegan Paul, London.

R Core Team, 2012. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. Available from <http://www.R-project.org/>, ISBN 3-900051-07-0.

Rawlings, J.O., Pantula, S.G., Dickey, D.A., 1998. Applied Regression Analysis: A Research Tool, second ed. Springer, New York.

Ronco, Jr., F., Edminster, C.B., Trujillo, D.P., 1985. Growth of ponderosa pine thinned to different stocking levels in northern Arizona. Res. Pap. RM-262. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experiment Station, 15 p.

Sargent, R.G., 1999. Validation and verification of simulation models. In: Farrington, P.A., Nembhard, H.B., Sturrock, D.T., Evans, G.W. (Eds.), Proceedings of the 1999 Winter Simulation Conference, 5–8 December 1999, Phoenix, Ariz. Institute of Electrical and Electronics Engineers, New York. pp. 39–48.

Shugart, H.H., 1984. A Theory of Forest Dynamics. Springer-Verlag, New York.

Snee, R.D., 1977. Validation of regression models: methods and examples. Technometrics 19, 415–428.

Somers, G.L., Oderwald, R.G., Harms, W.R., Langdon, O.G., 1980. Predicting mortality with a Weibull distribution. For. Sci. 26, 291–300.

Spur, S.H., 1952. Forest Inventory. Ronald Press, New York, 476 p.

Spurr, S.H., Barnes, B.V., 1980. Forest Ecology, third ed. John Wiley & Sons, New York.

Stage, A.R., 1976. An expression for the effect of slope, aspect and habitat type on tree growth. For. Sci. 22 (4), 457–460.

Uzoh, F.C.C., 2001. A height increment equation for young ponderosa pine plantations using precipitation and soil factors. For. Ecol. Manage. 142 (1–3), 191–201.

Uzoh, F.C.C., Oliver, W.W., 2006. Individual tree height increment model for managed even-aged stands of ponderosa pine throughout the western United States using linear mixed effects models. For. Ecol. Manage. 21 (1-3), 147–154.

Uzoh, F.C.C., Oliver, W.W., 2008. Individual tree diameter increment model for managed even-aged stands of ponderosa pine throughout the western United States using a multilevel linear mixed effects model. For. Ecol. Manage. 256 (3), 438–445.

Van Mantgem, P.J., Stephenson, N.L., Mutch, L.S., Johnson, V.G., Esperanza, A.M., Parsons, D.J., 2003. Growth rate predicts mortality of Abies concolor in both burned and unburned stands. Can. J. For. Res. 33, 1029–1038.

Wood, S.N., 2006. Generalized Additive Models: An Introduction with R. Chapman & Hall/CRC, New York, New York, USA.

Woodall, C.W., Grambsch, P.L., Thomas, W., 2005. Applying survival analysis to a large-scale forest inventory for assessment of tree mortality in Minnesota. Ecol. Model. 189, 199–208.

Wright, R.D., 1972. Validating dynamic models: an evaluation of tests of predictive powers. In: Proceedings of 1972 Summer Computer Simulation Conference, 13–16, June 1972, San Diego, Calif. Simulation Councils, La Jolla, California, USA.

Wunder, J., Reineking, B., Matter, Jean-Francçois, Bigler, C., Bugmann, H., 2007. Predicting tree death for *Fagus sylvatica* and *Abies alba* using permanent plot data. J. Veg. Sci. 18, 525–534.

Wyckoff, W.R., 1990. A basal area increment model for individual conifers in the northern Rocky Mountains. For. Sci. 36 (4), 1077–1104.

Yang, Y., Titus, S.J., Huang, S., 2003. Modeling individual tree mortality for white spruce in Alberta. Ecol. Model. 163, 209–222.

Yang, Y., Monserud, R.A., Huang, S., 2004. An evaluation of diagnostic tests and their roles in validating forest biometric models. Can. J. For. Res. 34, 619–629.

Zeide, B., 1991. Self-thinning and stand density. For. Sci. 37, 517–523.

Zeide, B., 2001. Natural thinning and environmental change: an ecological process model. For. Ecol. Manage. 155, 165–177.

Zeide, B., 2002. Density and the growth of even-aged stands. For. Sci. 48 (4), 743–754.

Zeide, B., 2004. In: Connor, Kristina F. (Ed.), Proceedings of the 12th Biennial Southern Silvicultural Research Conference. Gen. Tech. Rep. SRS–71. U.S. Department of Agriculture, Forest Service, Southern Research Station, Asheville, NC. 594 p.