

TWENTY FIVE YEARS LONG SURVIVAL ANALYSIS OF AN INDIVIDUAL SHORTLEAF PINE TREES

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A semi parametric cox proportion hazard model is preferred when censored data and survival time information is available (Kleinbaum and Klein 1996; Alison 2010). Censored data are observations that have incomplete information related to survival time or event time of interest. In repeated forest measurements, usually observations are either right censored or interval censored. Interval censoring occurs if the exact year of tree death is unknown, since measurement periods are typically longer than one year. Right censoring occurs if tree has not died at the end of the study.

Site index is generally assumed to be static over time while variables such as diameter, basal area, and crown ratio change over time are termed time varying covariates in the Cox model. The extended Cox model does not requires the assumption of proportional hazard and is appropriate to model time dependent nature of mortality with censoring of observations (Fisher and Linn 1999; Hosmer and others 2008). This model tests covariates for their significance with regard to individual tree survival. Thus we used the Cox extended model to identify effects of prognostic and protective variables on the survival of shortleaf pine for two data sets; 1) No ice damage: plots excluded having an ice damage event, and 2) all plots after an ice damage event (ice damage occurred during the fourth measurement).

A growth study of natural stands of shortleaf pine (*Pinus Echinata* Mill.) that was measured 6 times from 1985 to 2014 provided an opportunity to investigate the influence of time dependent covariates on the survival of individual trees. Over 200 permanent plots located in naturally occurring shortleaf pine forests on the Ozark and Ouachita National Forests were measured every 4 to 7 years. For details see Lynch and others (1999). The first measurement was conducted in 1985-1987, and the last (sixth) measurement occurred in between 2012-2014. The total sample included 208 plots that were 0.08 hectare (1/5th of an acre) in size. An ice storm in 2000 (during the 4th measurement) caused considerable damage on 111 of these plots.

Cox model is widely used (Fisher and Linn 1999; Alison 2010) in the biomedical field with an assumption: a) a study starts at t_0 and individual clinic visits occur at intervals where covariates (e.g. blood pressure, body weight) are recorded at each visit, b) an event occurs (e.g. glaucoma) between the visits, and exact time is unknown (interval censoring), and c) subjects are right censored and/or interval censored. Similar, assumption were made for tree mortality data while modelling Cox time dependent model. The standard Cox model (Eq. 1) assumes that hazard ratio (H_{zr}) is proportional between groups, while extended Cox model (time dependent model) (Eq. 2) assumes that H_{zr} is not proportional and depends upon time (Fisher and Linn 1999; Hosmer and others. 2008). The H_{zr} is the ratio of the hazard rate in the one group versus another group. The hazard rate is the probability that the event of interest will occur in the next time interval, divided by the length of that interval.

$$h(t) = h_0(t) \exp\left(\sum_{i=1}^K \beta_i x_i\right) \quad (1)$$

$$h(t, x) = h_0(t) \exp\left(\sum_{i=1}^K \beta_i x_i + \sum_{i=1}^k \gamma_i x_i g_i(t)\right) \quad (2)$$

where $h(t)$ is hazard function at time t , $h_0(t)$ is base line hazard function, $h(t, x)$ is hazard function for x covariate that depends on time t , β , is the parameter to be estimated associated with variables, x_i is number of variables, γ_i is a parameter associated the variable x_i of the time dependent function ($g_i(t)$); t is the upper time interval in month for the period. We tested to see if $\gamma = 0$; if $\gamma = 0$, then the model was proportional hazard model, otherwise it was a time dependent model.

The mortality rate for measurement periods was an average of 4 percent with no ice storm, and 4.2 percent after ice damage. The Schoenfeld residual test showed that the parameter estimates of a few of the univariate models violated the assumption of proportionality of hazards and therefore were time dependent models

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(table 1). The parameter estimates of the multivariate time dependent model for both no ice damage and after ice damage indicated violation of an assumption of proportionality of hazard while the fixed covariate *SIND* did not (table 1). A semi parametric 'Cox proportional extended model' including time dependent covariates, showed an agreement for hazard ratio assignment of 84 percent for with no ice damage, and 90 percent after an ice damage event (fig. 1).

No Ice Damage: The univariate model with variable *RAQD* and *PLTHT* appeared highly significant as time dependent model (table 1). The univariate model with *RAQD* performed as prognostic model while model with *PLTHT* performed as protective model (table 1). The multivariate model with the variables *RAQD*, *CRT*, *SIND* and interaction of *DBH* and log of *TIME2* (upper bound of time interval) was found to be the best time dependent model (table 1). The multivariate model had hazard ratio assignment of 84 percent for plots and time periods with no ice damage.

After Ice Damage: The univariate model with *RAQD*, *BAHA*, *DBH*, and *PCTL* was highly significant ($p < 0.0001$) as time dependent model (table 1). Univariate models using *RAQD*, *BAHA*, and *PCTL* performed as prognostic (associated with increased mortality) models while a model with *DBH* performed as protective model (associated with reduced mortality) (table 1). The multivariate model included *RAQD*, *PLTHT*, *SIND*, *PCTL* and interaction *PLTHT* with *TIME2* was found to be best time dependent model (table 1). The mortality risk of an individual tree belonging to *PCTL1* was 10 times higher than a tree belonging to *PCTL0* (table 1). The multivariate model had hazard ratio assignment of 90 percent for plots and time periods after ice damage.

The position of a tree (*RAQD*), and site productivity (*SIND*) were important prognostic variables in determining survival of an individual shortleaf pine. The variable crown ratio (*CRT*) behaved as significant protective variable, and had marginally increasing influence in survival probability. The influence of *RAQD*

Table 1—Prognostic ($H_{zr} > 1$) and protective ($H_{zr} < 1$) behavior of variables in univariate, and multivariate time dependent models for no ice damage, and after ice damage

Data sets	Univariate models			Multivariate model		
	Variables	Hazard ratio	Probability	Variables	Hazard ratio	Probability
No Ice	RAQD ⁺	4.2146	80.82	RAQD ⁺	2.1029	67.77
	PLTHT ⁺	0.9036	47.47	CRT ⁺	0.1204	10.75
	BAHA	1.0578	51.40	SIND	1.1718	53.96
	QDHA	0.9289	48.16	DBH(log(Time2)) ⁺	0.9773	49.43
	PAG	0.9708	49.26			
	DBH	0.8765	46.71			
	HT ⁺	0.8388	45.62			
	CRL	0.5801	36.71			
After Ice	RAQD ⁺	3.923	79.29	RAQD ⁺	5.1359	83.70
	CRT ⁺	0.0003	0.03	PLTHT ⁺	1.5754	61.17
	PLTHT ⁺	1.0228 [#]	50.56	PLTHT(TIME2) ⁺	0.9932	49.83
	BASQM ⁺	0.0044	0.44	SIND	1.1145	52.71
	BAHA ⁺	1.031	50.76	PCTL1 ⁺	9.5058	90.48
	DBH ⁺	0.9609	49.0			
	DAG	0.0091	0.90			
	PCTL ⁺	13.256	92.99			

Note: Univariate models are without fixed covariate '*SIND*', and multivariate models were with fixed covariate '*SIND*'. *No ice* = Data set with all plots (observations) that had no ice damage; *After Ice* = Data set with all plots (observations) after ice damage event. [#]Coefficient estimate was significant with $p < 0.05$, while other estimates were significant with $p < 0.0001$.

⁺ Variable appeared significant to violate an assumption of proportionality of hazard. Hazard ratio are based on exp (coefficient). *RAQD* = Ratio of quadratic mean diameter to diameter at breast height (dbh); *PLTHT* = Average dominant and co-dominant height (m); *CRL* = Crown length (m); *CRT* = Crown Ratio; *SIND* = Site Index(m); *BAHA* = Stand basal area per hectare (m^2ha^{-1}); *QDHA* = Quadratic mean diameter (cm); *PAG* = Plot age (years); *DBH* = Diameter at breast height (cm); *DAG* = Ratio of dbh to plot age (cm yr⁻¹); *HT* = Individual tree height (m); *TIME2* = Time at upper interval (months); *PCTL* = Percent of crown loss due to ice damage; *PCTL0* = Crown loss 0-50%; *PCTL1* = Crown loss >50%.

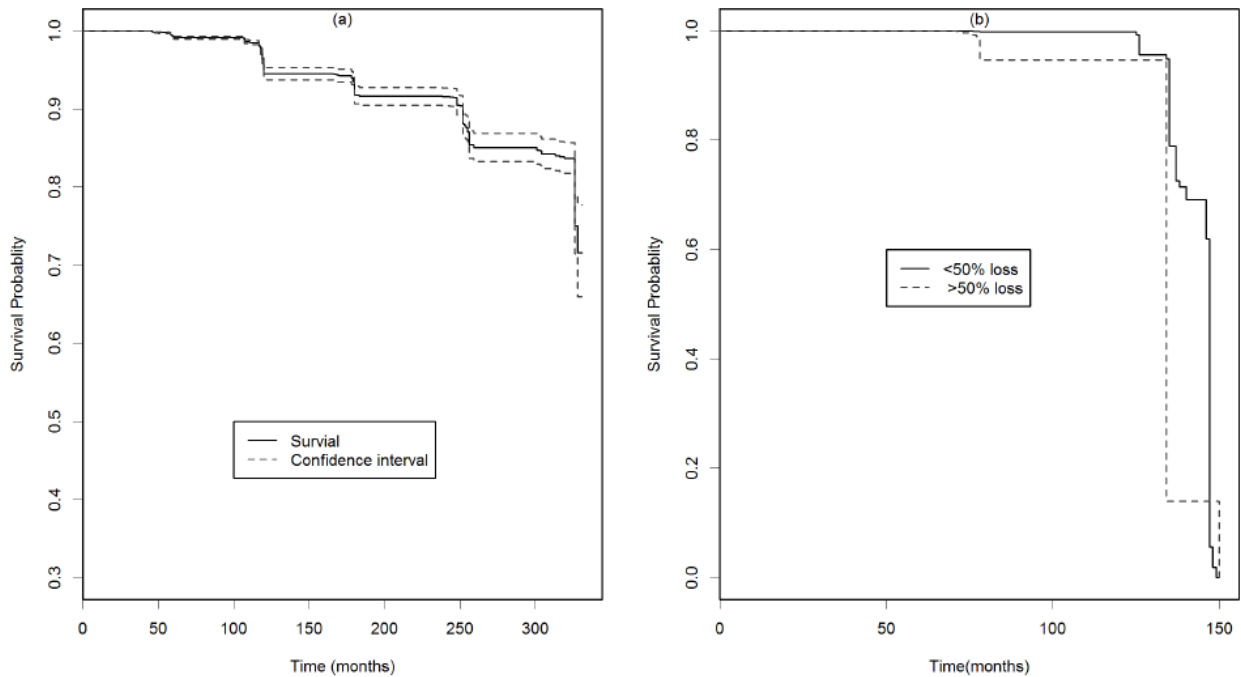


Figure 1—Survival probability by potential by multivariate model with fixed covariate for no ice damage (a) and after ice damage (b). In figure (b) an estimated median survival time ($S(t_{0.5}) = 0.5$) for trees that died during the study was 146 months for *PCTL0*, and was 134 months for *PCTL1*.

in mortality increases over the time. Though average dominant plot height (*PLHT*) was a prognostic variable, its influence decreases over time. An individual tree with greater than 50 percent crown loss has higher mortality risk than a tree with less than or equal to 50 percent crown loss.

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