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# Applying survival analysis to a large-scale forest inventory for assessment of tree mortality in Minnesota

C.W. Woodall [a,*], P.L. Grambsch [b], W. Thomas [b]

[a] *USDA Forest Service, North Central Research Station, St. Paul, MN 55108, USA*
[b] *Division of Biostatistics, School of Public Health, University of Minnesota, Minneapolis, MN 55407, USA*

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**Abstract**

Tree mortality has traditionally been assessed in forest inventories through summaries of mortality by location, species, and causal agents. Although these methods have historically constituted the majority of tree mortality summarizations, they have had limited use in assessing mortality trends and dynamics. This study proposed a novel method of applying survival analysis for the purpose of analyzing tree mortality in forest inventories. Individual tree size and growth increments were used to estimate survival and hazard functions for a forest inventory for the state of Minnesota. These estimates provided regional mortality and variance estimates by diameter at breast height (DBH) and diameter growth classes (ΔDBH) between successive inventories. Comparisons of survival/hazard curves for various tree populations and tests of effects of covariates on individual survival curves were conducted allowing for mortality hypothesis testing across user-defined tree populations (i.e., species, location, stand conditions, and damage agents). Survival analysis techniques, facilitated by the variables of DBH and ΔDBH, may provide foresters with the ability to test tree mortality hypotheses and summarize regional tree mortality trends.


*Keywords:* Mortality; Survival analysis; Hazard function; Forest inventory

## 1. Introduction

Tree mortality in forest inventories has traditionally been assessed using relatively simple summary statistics. Mortality information available to foresters has typically included losses in timber volume due to mortality, summaries of mortality causal agents, spatial locations of mortality, and mortality trends by species (see Leatherberry et al., 1995). Currently, most forest health reports for state and other large-scale forest inventories use this mortality assessment methodology (MDNR, 1994; Mutch and Parsons, 1998). More in-depth mortality analysis has historically only been facilitated through development of individual tree mortality logistic models, a technique that has had limited use in national inventories (Monserud and

* Corresponding author. Tel.: +1 651 649 5141; fax: +1 651 649 5140.
*E-mail address:* cwoodall@fs.fed.us (C.W. Woodall).

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Sterba, 1999; Fridman and Stahl, 2001) and may be inadequate for broadly defining mortality dynamics (Eid and Tuhus, 2001). Although remotely sensed information and geographic information systems have greatly aided analysis of forest mortality, the basic analytical methodologies of forest mortality assessment have only slowly evolved (Hawkes, 2000).

The forest sciences have historically focused on developing individual tree mortality sub-models for incorporation into growth and yield models (Stage, 1973; Daniels and Burkhart, 1975; Hamilton and Edwards, 1976; Monserud, 1976; Buchman et al., 1983). Although other sciences that monitor populations of living organisms, such as the veterinary and medical sciences, have developed methodologies to assess mortality beyond that of the individual, the forest sciences have relatively few methodologies for assessing tree population mortality (Hawkes, 2000). Commonly used forest mortality analytical techniques lack methodology for incorporating the time-dependent nature of tree mortality, hypothesis testing, censoring of observations, and tests for effects of covariates (i.e., stand basal area and crown ratio). Given the diseases and epidemics that have greatly altered our forest ecosystems (e.g., Chestnut Blight [*Cryphonectria parasitica*] and Dutch elm disease [*Ceratocystis ulmi*]) and future forest health issues that may occur (Sudden Oak Death Syndrome [*Phytophthora ramorum*], Asian longhorned beetle [*Anoplophora glabripennis*]), novel techniques for assessing large-scale tree mortality and forest decline would benefit forest scientists and managers alike.

Analytical methods developed by the medical sciences, collectively termed survival analysis, may provide the basis for development of new forest mortality analytical techniques (Harcombe, 1987; Zens and Peart, 2003). Survival analysis is most often defined as a class of statistical methods for studying the occurrence and timing of events—most often death (Berkson and Gage, 1950; Cox and Oakes, 1984; Allison, 1995). Survival analysis is unique in that it allows for censoring of observations (lack of exact time of death) and inclusion of time-dependent covariates, in addition to dealing with non-normal distributions (Collett, 1994; Allison, 1995). Waters (1969) first proposed using survival analysis to address forest mortality issues, but such applications have been restricted mainly to forest inventories in even-aged forest plantations (Morse and Kulman, 1984; Amateis et al., 1997; Volney, 1998; Wyckoff and Clark, 2000), forest research plots (Reams et al., 1988; Burgman et al., 1994; Preisler and Slaughter, 1997), or stand table projections (Rose, 2002). Although there has been significant work on the development of estimation procedures for survival and hazard functions in forest research plots (Preisler and Slaughter, 1997; Volney, 1998) and in relation to diameter growth (Bigler and Bugmann, 2004a,b), survival analysis techniques have not been widely applied to forest inventory analyses due to the inherent lack of detailed time and age information for large-scale inventories (Flewelling and Monserud, 2002). Given the current lack of baseline forest inventory mortality analyses techniques (Manion and Griffin, 2001) and the potential that survival analysis offers (Harcombe, 1987; Hawkes, 2000; Zens and Peart, 2003), a re-examination of the basics of survival analysis in the context of a large-scale forest inventory is warranted and may refine analysis of tree mortality in Minnesota.

The primary goal of this study is to estimate and interpret the central functions of survival analysis, survival, and hazard functions, on a time scale defined by growth in diameter at breast height ($\Delta$DBH), for a USDA Forest Service Forest Inventory and Analysis program (FIA) inventory in the state of Minnesota. The study has specific objectives:

1) to use DBH and $\Delta$DBH in applying survival analyses techniques to forest inventories;
2) to determine if survival/hazard functions can represent actual mortality trends in a manner practical for ecological interpretation;
3) to determine utility of testing for differences between survival/hazard functions and the effects of covariates stratified by species, damage agents, and spatial locations.

## 2. Methods

### 2.1. Data

The data for this study came from two FIA periodic inventories for the state of Minnesota where sample trees were surveyed in 1977 and re-measured in 1990

Table 1
Summary of FIA inventory used in survival analysis, Minnesota 1977–1990

| Species group | Species | Total number of trees | Number of trees that died |
|---|---|---|---|
| Red and Jack Pine | *Pinus resinosa*, *Pinus banksiana* | 3935 | 734 |
| Black Spruce and Balsam Fir | *Picea mariana*, *Abies balsamea* | 14972 | 5035 |
| Maples | *Acer saccharinum*, *Acer saccharum* | 2747 | 365 |
| Balsam Poplar | *Populus balsamifera* | 4448 | 1822 |
| Paper Birch | *Betula papyrifera* | 8603 | 2443 |
| American elm | *Ulmus americana* | 3829 | 3073 |
| Aspen | *Populus tremuloides* | 21303 | 7821 |
| Red Oak | *Quercus rubra* | 2962 | 520 |

(Table 1). The periodic sampling design for the Minnesota inventory is detailed by NCFES (1977, 1990). Individual trees (observations) were included that met the following criteria: alive at time one (1977) and either dead or alive at time two (1990), DBH >13.0 cm at time one, and no anthropomorphic mortality. Additionally, to streamline the relatively large datasets, only the most common species were selected (Table 1). Individual tree attributes from the FIA inventory measured at time one were included as predictors of mortality in this study: DBH (cm), crown ratio (CRAT), crown class (CC), plot basal area (TOTBA), plot basal area larger than subject tree (BAL), and damage. If a tree was dead at time two then its DBH was set equal to the DBH at time two or the DBH at time one, whichever was larger. Since a tree's DBH may shrink following death, an estimate of the maximum DBH the tree attained before death would better benefit survival analysis than an estimate of a decaying bole diameter. CRAT is the ratio of a tree's live crown length to total height. CC is a measure of a tree's dominance in relation to adjacent trees in the same stand and is coded as follows: 1, open grown; 2, dominant; 3, codominant; 4, intermediate; 5, suppressed (NCFES, 1990). TOTBA were calculated as the sum of cross-sectional areas of live tree boles at breast height at time one scaled to a per unit area basis, while BAL was the same as TOTBA except with exclusion of basal area of trees with DBH's smaller than the subject tree. Insect or disease tree damage was recorded at time one based on field observation protocols (NCFES, 1990). ΔDBH was calculated as the difference in DBH between time one and time two. For trees that died during the re-measurement interval (censored), ΔDBH represents less of an average growth rate.

### 2.2. Analysis

The survival and hazard functions, central to survival analysis, are used to quantify the probability distribution of mortality in a population (Muenchow, 1986). The survival function is defined as (Berkson and Gage, 1950; Cox and Oakes, 1984; Collett, 1994),

$$S(t) = P(T \geq t), \tag{1}$$

where $S(t)$ is the probability that a death occurs at some time $T$ at least as great as time $t$, but is not constrained except for being greater than 0.

The hazard function is an instantaneous mortality rate and hence is a conditional probability defined as (Cox and Oakes, 1984; Collett, 1994),

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \leq T \leq t + \Delta t | T \geq t)}{\Delta t}, \tag{2}$$

where $h(t)$ is the probability that death occurs exactly at time $t$, given that it has not occurred before then.

The survival function may be estimated non-parametrically by using the life-table method given by (Cox and Oakes, 1984; Allison, 1995),

$$\hat{S}(t_i) = \prod_{j=1}^{i-1} (1 - h_j), \tag{3}$$

where for interval $i$, $t_i$ is the start of time and $h_i$ is the conditional probability of death. For $i = 1$ and hence $t_i = 0$, the survival probability is set to 1.0.

The life-table non-parametric estimate of the hazard function at the midpoint of each time interval is given by (Cox and Oakes, 1984; Allison, 1995),

$$h(t_{i\mathrm{m}}) = \frac{d_i}{b_i \left( n_i - \frac{w_i}{2} - \frac{d_i}{2} \right)}, \tag{4}$$

where for the $i$th interval, $t_{im}$ is the midpoint, $d_i$ the number of deaths, $b_i$ the width of the interval, $n_i$ the number of individuals at the beginning of the interval, and $w_i$ is the number of cases censored (exact time of death cannot be ascertained) within the interval. *Note*, the survival and hazard functions are mathematical functions of each other; given one, you can compute the other.

The null hypothesis, that the survival functions are the same for two groups of individuals, may be tested by the non-parametric log-rank test statistic given by (Allison, 1995),

$$U_L = \sum_{j=1}^{r}(d_{1j} - e_{1j}), \quad (5)$$

where $U_L$ is the summation over all unique event times (in both groups) and there are a total of $r$ such times. $d_{1j}$ is the number of deaths that occur in group 1 at time $j$ and $e_{1j}$ is the expected number of events in group 1 at time $j$. The expected number of events is given by $n_{1j}d_j/n_j$, where $n_j$ is the total number of cases that are at risk just prior to time $j$, $n_{1j}$ the number at risk just prior to time $j$ in group 1, and $d_j$ is the total number of deaths at time $j$ in both groups. Squaring and dividing $U_L$ by the estimated variance provides a chi-square statistic. Additionally, log-rank tests may be generalized to test whether quantitative covariates are associated with survival times.

As evidenced in survival analysis formulations, time to an event is the defining component of survival methods. Hence, the major obstacle cited as limiting the application of survival analysis to forest inventories is the lack of specific tree ages and the censoring of tree mortality (Flewelling and Monserud, 2002). However, knowledge of age is not necessary for implementation of survival analyses (Allison, 1995). Any measurement unit that indicates changes in an individual's status between re-measurements may replace the traditional survival analysis variables of age and time. For forest inventories that re-measure trees at regular intervals (e.g., national inventories, see Gillespie, 1999; Fridman and Stahl, 2001), DBH and ΔDBH may assign individual trees within a population to classes defined by tree size and growth. Whereas medical studies may determine survival functions for demographic cohorts across calendar years, forest inventory survival functions may be determined for DBH classes (Harcombe, 1987) across growth classes.

In this study, the "clock" starts at the first forest inventory, when a subject begins to be "at risk" for the event or begins to be monitored for the event. Stating this in terms of DBH, the clock is ΔDBH (the increase in DBH from initial survey). Other studies (Bigler and Bugmann, 2004a,b) have found some success in using predicted ΔDBH to refine estimates of time of tree death. Our survival function $S$(ΔDBH) gives the probability that a tree will continue to live until its diameter has increased by at least ΔDBH. The "time interval" of our hazard function is diameter growth of 4 cm. For example, $S$(8 cm) estimates the proportion of the population of trees that will survive to increase their DBH by 8–12 cm. This hazard function, where $k$ = ΔDBH, can be interpreted as a ratio of the number of deaths per 4 cm growth in a large population of trees that are $k$ cm larger in DBH than at the first measurement. Hence, for all previously stated formulations of the non-parametric survival and hazard function estimators and log-rank tests (Eqs. (3)–(5)), our study substituted ΔDBH for time.

Several software packages produce estimates of the survival and hazard functions. In this study, the PROC LIFETEST (SAS, 1999) and its life-table estimation method were used. Trees were grouped by initial DBH into 10-cm diameter classes and grouped by ΔDBH into 4-cm intervals. The survival and hazard functions (Eqs. (3) and (4)) were compared for their forest science applicability. The hazard function was examined for three subsets of trees: trees suffering from disease, trees suffering from insects, and certain species groups. In addition, the survival function was further examined in terms of equality over function strata (species groups and inventory unit locations; see NCFES, 1990) and in terms of effects of covariates (CRAT, CC, BAL, and TOTBA) using the log-rank tests (available in SAS PROC LIFETEST) (Eq. (5)).

## 3. Results

The survival and hazard functions were estimated separately for five initial DBH classes for selected species in the 1977–1990 Minnesota inventory (Figs. 1 and 2). For the cumulative distribution of survival functions in this study, a function value of 0.6

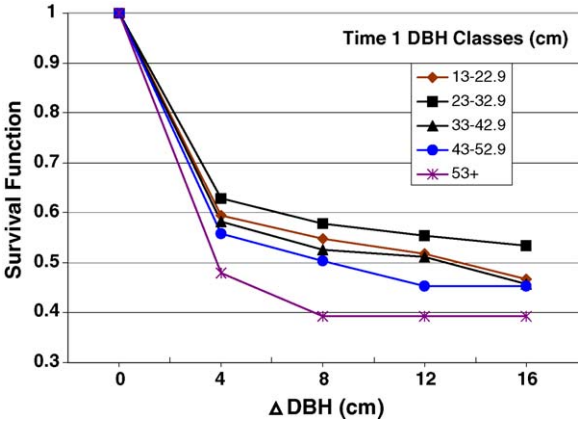


Fig. 1. Survival functions for time one diameter classes by ΔDBH.

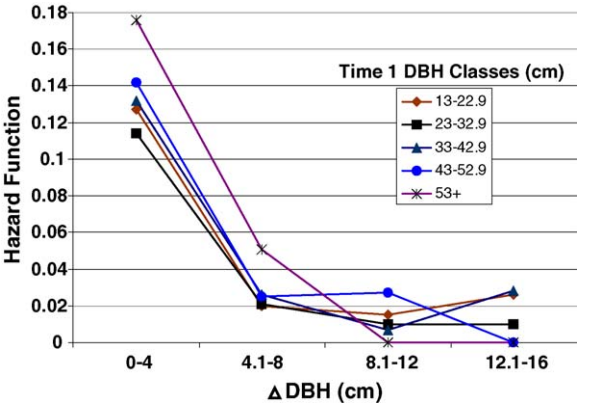


Fig. 2. Hazard functions for time one diameter classes by ΔDBH.

for a 0–4 cm ΔDBH does not indicate a high survival probability; rather it shows a substantial drop in the likelihood of survival to the next ΔDBH class (Fig. 1). Regardless of initial DBH, the greatest increase in cumulative probability of mortality was seen in trees with the least periodic diameter increment. Larger trees suffered greater mortality than smaller trees as evidenced by the ordering of the survival functions (Fig. 1). Hazard functions varied both by time one DBH classes and ΔDBH (Fig. 2). For all five initial size classes, the hazard of death was greatest in trees with the least periodic diameter increment, with hazards dropping abruptly and remaining fairly constant in trees with substantial diameter growth (Fig. 2). The largest trees with the least growth had the greatest mortality, evidenced by their high mortality hazards and their steeply descending slopes (Fig. 2).

The hazard functions for trees suffering from insect and disease damage were determined separately (Fig. 3A and B). For insect damaged trees, the smallest diameter trees had the greatest hazard of death, with the hazard decreasing precipitously with increases in ΔDBH (Fig. 3A). Trends in hazard functions for trees suffering disease damage were distinctly different from the insect damaged trees (Fig. 3B). The largest trees had the highest hazard of death for the first two classes of ΔDBH, while hazards were more evenly distributed among all size classes for trees growing substantial increment (Fig. 3B). Small and mid-sized trees that had the greatest diameter growth were still at risk from death, possibly resulting from disease damage (Fig. 3B).

Hazard functions for the 23.0–32.9 (cm) DBH class, stratified by species group, were determined for

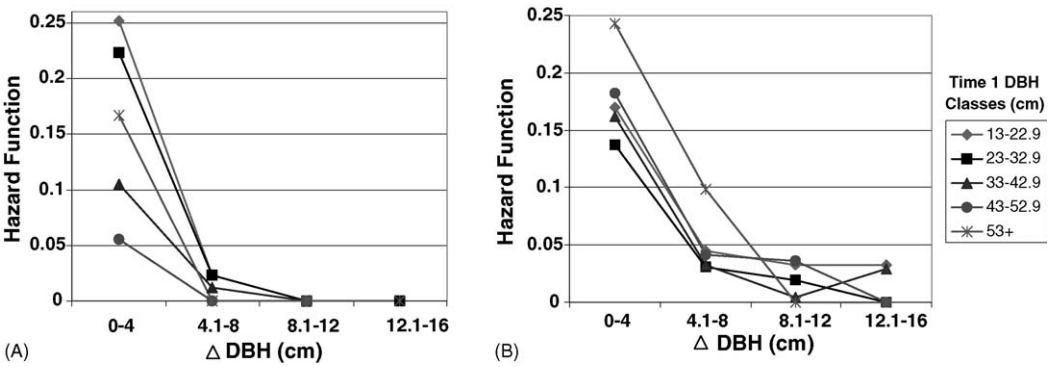


Fig. 3. Hazard functions for trees suffering from insect damage (A) and for trees suffering from disease (B).

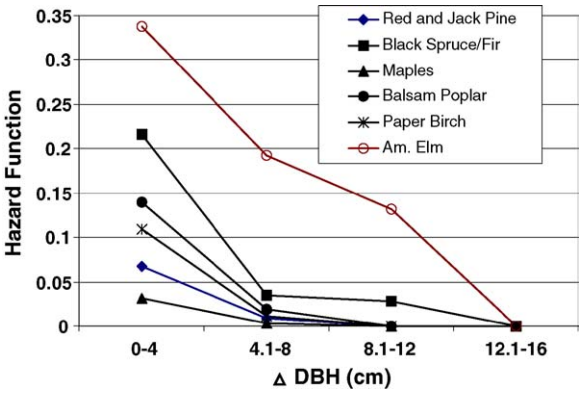


Fig. 4. Hazard functions for time one DBH class 23–32.9 cm for various Minnesota tree species.

assessment of interspecific mortality trends (Fig. 4). Risk of mortality was distinctly different between all species groups across all classes of ΔDBH (Fig. 4). American elm had the highest hazard function estimates across all classes of ΔDBH, while maples had the lowest hazard function estimates (Fig. 4). Possible differences between spatial locations and interspecific hazard functions (test of homogeneity of survival function), in addition to effects of covariates (i.e., stand density) by species group, were examined through log-rank tests (Tables 2 and 3). There were significant differences in survival functions among the inventory units of Minnesota forestland (Aspen-Birch, Northern Pine, Central Hardwood, and Prairie) (NCFES, 1990) for the smaller red and jack pines (Table 2). For most of the maple diameter classes, there was no significant difference among survival functions (Table 2). Elms had significant survival function differences among ecological units for the smallest and largest trees (Table 2). Obvious differences in the degrees of freedom among ecological units is attributable to the lack of red and jack pine species among certain units, especially for the larger diameter classes (Table 2). Log-rank tests were conducted for effects of covariates on survival functions by species and time one DBH classes (Table 3). Effects of covariates (CRAT, CC, TOTBA, and BAL) were predominantly significant in the smaller DBH classes, regardless of species (Table 3). For hardwoods, crown factors were more often significant covariates than stand density measures (Table 3). For conifers, the opposite was usually the case: stand density covariates were significant in more individual cases than crown factors (Table 3).

## 4. Discussion

A longitudinal unit can be any unit that measures a variable's transition from one state (i.e., class or condition) to another (Collett, 1994). The greatest hurdle in applying survival analytical techniques to forest inventories is finding appropriate longitudinal units to

Table 2
Test for equality between ecological units, by DBH class and species group, Minnesota 1977–1990

| Species | DBH class (cm) | Chi-square | Degree of freedom | *p*-Value |
|---|---|---|---|---|
| Red and jack pine | 13.0–22.9 | 11.81 | 2 | 0.0027 |
| | 23.0–32.9 | 19.41 | 2 | 0.0001 |
| | 33.0–42.9 | 7.53 | 2 | 0.0232 |
| | 43.0–52.9 | 0.41 | 2 | 0.8165 |
| | 53.0+ | 0.36 | 1 | 0.5471 |
| Maples | 13.0–22.9 | 2.54 | 3 | 0.4686 |
| | 23.0–32.9 | 3.56 | 3 | 0.3136 |
| | 33.0–42.9 | 9.81 | 3 | 0.0203 |
| | 43.0–52.9 | 6.38 | 3 | 0.0946 |
| | 53.0+ | 5.24 | 3 | 0.1553 |
| American elm | 13.0–22.9 | 16.18 | 3 | 0.0010 |
| | 23.0–32.9 | 13.78 | 3 | 0.0032 |
| | 33.0–42.9 | 5.84 | 3 | 0.1198 |
| | 43.0–52.9 | 8.12 | 3 | 0.0436 |
| | 53.0+ | 14.44 | 3 | 0.0024 |

Table 3
Log-rank test for effects of covariates on survival functions by species and DBH class, Minnesota 1977–1990 (X indicates $p$-value <0.05)

| Species | Variable | DBH classes (cm) | | | | |
|---|---|---|---|---|---|---|
| | | 13.0–22.9 | 23.0–32.9 | 33.0–42.9 | 43.0–52.9 | 53.0+ |
| Red and jack pine | CRAT | X | X | X | | |
| | CC | X | | | | |
| | TOTBA | | X | X | X | |
| | BAL | X | | X | | |
| Black spruce/fir | CRAT | X | X | X | | |
| | CC | | X | | | |
| | TOTBA | X | X | | | |
| | BAL | X | X | | | |
| Maples | CRAT | X | X | X | X | X |
| | CC | X | X | X | X | X |
| | TOTBA | | X | | | |
| | BAL | | | X | | |
| Balsam poplar | CRAT | X | X | X | X | |
| | CC | X | X | | | |
| | TOTBA | | X | | | X |
| | BAL | X | | X | | |
| Paper birch | CRAT | X | X | X | | |
| | CC | X | X | X | X | |
| | TOTBA | | | | | |
| | BAL | X | | | | |
| American elm | CRAT | X | X | | | |
| | CC | X | X | X | X | |
| | TOTBA | X | | | X | X |
| | BAL | X | | X | | |

quantify survival probabilities and mortality hazards (Zens and Peart, 2003). If time or ages are used as longitudinal units in forest inventory analyses, a number of problems may be encountered as evidenced by previous work in forest survival analysis (Harcombe, 1987; Burgman et al., 1994; Preisler and Slaughter, 1997; Volney, 1998). First, all observations are censored. The exact time of tree death is uncertain with the inventory re-measurement date often serving as the longitudinal measure. Second, the survival function curve is partially dependent on when and where the measurements were taken. For example, if the bulk of mortality is located in a certain area of the state that is inventoried at a discrete point in time, then the resulting survival curve will be biased if time is used. Third, the age of a tree is difficult to estimate in large-scale forest inventories. However, DBH is a quantity that hypothetically increases with time until a tree dies. Harcombe (1987) suggested that using a tree's diameter may be viewed as "stage-based," where life-tables estimate the probability of individual tree growth projecting a tree forward through stages (DBH classes). Although DBH is not a perfect predictor of tree age (especially in uneven-aged stands), tree diameter was used as a hypothetical surrogate for age or "stage" in this study's survival analysis. Likewise, ΔDBH, although not an exact surrogate for time, may serve as a "stopwatch" for individual trees in this study. At the start (time one), the ΔDBH of all trees is 0. At the time of re-measurement (time two) the "stopwatch" is stopped and trees are assigned to classes of ΔDBH. Time (years) may greatly relate to the survivalship of humans, while tree growth over intervals of time (i.e., annual diameter growth) may be a more meaningful metric in forest ecology. Bigler and Bugmann (1994a) found that using ΔDBH models to refine estimates of time of death greatly improved logistic mortality models. Unfortunately, as suggested by this study, the longer the inventory re-measurement in-

terval the greater the possibility that ΔDBH may inaccurately reflect time due to the censoring of tree death and variable tree growth rates (particularly in uneven-aged stands). While previous studies at smaller scales and in even-aged stand conditions have been able to develop rather flexible survival/hazard functions using individual tree age and time (Burgman et al., 1994; Preisler and Slaughter, 1997; Volney, 1998), this study's use of tree size and growth allowed survival analyses to be conducted on large-scale forest inventories and warrants future evaluation and possible application.

There are numerous estimation procedures for the survival and hazard functions, each with its own advantages and drawbacks. This study used the elementary life-table estimation procedure as a first attempt to apply survival analysis techniques to large-scale forest inventories, a technique first suggested by Harcombe (1987). The life-table approach allowed non-parametric estimation of survivorship, the ability to compare survivorship among stratified sample units, and the ability to test association between covariates and survivorship. Using the life-table estimation procedure as a first attempt, the survival and hazard functions initially appear to offer a new procedure for analysis of forest mortality. The survival function quantifies mortality cumulatively through the diameter distribution, while the hazard function may display specific DBH midpoint mortality rates. As evident from the survival and hazard function curves for Minnesota, DBH classes with divergent or atypical mortality trends may be readily identified. Divergences of survival function curves from the "typical" function bounds for specific tree populations may help identify problem areas in a rapid, statistically defensible manner. As suggested by Manion and Griffin (2001), the quantification of "normal" rates of mortality across diameter classes helps identify atypical mortality trends as soon as they arise. The hazard and survival functions can together provide an initial assessment of tree mortality for forest inventories as long as the survey interval of time is approximately the same between re-measurements. Sampling intervals, such as 13 years in this study, will affect ΔDBH class width and ultimately the interpretation or application of survival analyses as demonstrated in this study.

Traditionally, insects and disease tree mortality has been expressed in terms of ratios of tree mortality. Hazard functions can be used for more detailed analysis of mortality dynamics for any tree population of interest. Study results indicate that there may be definitive differences between hazard functions for trees suffering from insect or disease damage. For Minnesota, although mortality from disease occurred predominantly in small, slow-growing trees, it affected all trees regardless of size or growth rates. Hazard functions indicated that there was little risk of death from insects for trees with substantial diameter growth, possibly indicating the relationship between a tree's vigor and resilience to insect attacks. He and Alfaro (2000) found that survival analysis was useful in analyzing tree resistance to pest attack; however, they also found that tree survival time was related to covariates not used in this study such as seasonal temperatures and precipitation. It should be noted that this study's hazard analysis is only valid if tree damage is assessed at inventory time one.

Hazard functions also allowed for a broad comparison of mortality risk rates among species and diameter classes. Although analysis using only one diameter class was conducted in this study, there were obvious differences in hazard functions among species. American elm, due to the widespread effects of Dutch elm disease, had the highest rates of hazard. In comparison, other species such as maples displayed no such widespread declines. This study's methodology may allow comparison of hazard functions between species over successive inventory cycles. Detection monitoring of atypical mortality may be aided through observing risks of mortality by species, DBH class, and ΔDBH class (hazard functions) in comparison to natural mortality distributions (U-shaped mortality curve; see Harcombe, 1987). For large-scale forest inventories, hazard functions may aid investigations between forest mortality and causal agents.

In addition to interpreting survival and hazard functions curves, log-rank tests of survival curves allowed for mortality hypothesis testing. Test for homogeneity of the survival function among the ecological units of Minnesota indicated that the survival function was significantly different among different spatial locations of tree populations (ecological regions). Additionally, the log-rank test for effects of covariates on the survival function, by species and time one DBH class, indicated that a host of covariates are significant based on species

and tree size. This study's covariates of tree mortality, although representing a small range of variability, included both individual tree health indicators (i.e., CRAT) and stand-level attributes (i.e., TOTBA). Since hardwoods may be more shade tolerant than conifers, individual tree characteristics (CC and CRAT) were more often significant covariates for hardwood mortality. As found in other mortality studies (Dobbertin and Brang, 2001), crown conditions may be an important predictor of individual tree mortality. However for conifers, their lack of shade tolerance was reflected in more significance of stand density covariates (TOTBA and BAL). The ability to associate individual tree traits with mortality hazard has enormous potential benefits for the study of natural processes (Zens and Peart, 2003) such as those found in forest ecosystems. Although covariate analysis in this study only allowed for tests of significance without the quantification of the magnitude or direction of covariate effects, the establishment of baseline information on significant covariates of tree mortality across tree species may allow for hypothesis testing.

## 5. Conclusions

Forest inventory mortality analyses have predominantly been focused on logistic regression modeling at the individual tree-scale and simple data summarizations at the landscape-scale. The apparent disparity in research efforts between forest ecosystem scales means few advances or technologies have been forwarded for analysis of forest mortality dynamics at large-scales. This study proposed an approach to large-scale forest mortality assessment involving combination of established survival modeling techniques (survival/hazard functions) with traditional quantifications of forest stand attributes (DBH distribution and diameter growth). As this study was a first-attempt to use DBH and $\Delta$DBH as surrogates for age and time in application of survival analysis in forest inventories, elementary survival analysis estimation procedures were utilized. However, this study's approaches may eventually lead to more efficient and statistically defensible assessments of tree mortality for tree populations across different forest types, locations, and suffering from varying damage agents.

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