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## The Effect of Nitrogen Fertilization and Rock Type on Individual Tree Mortality

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ABSTRACT. An individual tree mortality model for nitrogen fertilized Douglas-fir (Pseudotsuga menziesii var. glauca (Beissn.) Franco) stands was developed using data from permanent research plots located throughout the inland Northwest. The proposed linear logistic model included the following independent variables: a set of dummy variables for the 5 rock types, a set of dummy variables for the 3 nitrogen fertilizer treatments, diameter at breast height, crown ratio, number of trees per hectare, and relative rank of tree size, defined by basal area in larger trees over basal area per ha. The results show that nitrogen fertilization and rock type significantly affect individual tree mortality. Trees growing on granitic and meta-sedimentary rocks exhibited greater probabilities of mortality than did those growing on other rocks. The probabilities of mortality for trees growing on sedimentary rocks were very low. The probabilities of tree mortality increased with increasing nitrogen fertilizer application rates. Finally, nitrogen fertilization response ratios for annual probability of tree mortality were estimated based on the mortality model. The response ratios were nearly constant (about 1.54) across a range of tree diameters for all rock types with the 224 kg N treatment. The response ratios were also nearly constant (about 2.50) across a range of tree diameters for all rock types with the 448 kg N treatment.

Additional Key Words: *Pseudotsuga menziesii* var. *glauca*, logistic function, mortality prediction.

Interior Douglas-fir (*Pseudotsuga menziesii* var. *glauca* (Beissn.) Franco) is important in a wide range of forest types for a wide array of non-timber values, and also plays a critical role in local and regional economies as a raw material for wood and paper products in the inland Northwest. Therefore, forest managers apply intermediate silvicultural treatments, such as cleaning, thinning, and fertilization, to Douglas-fir stands to achieve specific management goals.

In the inland Northwest, forest fertilization research began in the early 1960's (Loewenstein and Pitkin 1963, Loewenstein and Pitkin 1971). Early work focused on growth response of grand fir (Abies grandis (Dougl.) Lindl.) and Douglas-fir stands to thinning and nitrogen fertilization in northern Idaho (Olson 1981, Scanlin and Loewenstein 1981, Shafii et al.1989). Recently, considerable research (Mika and Moore 1991, Shafii et al.1990, Stage et al. 1990, Mika and Vander Ploeg 1991, Moore et al. 1991, Mika et al. 1992, Moore et al. 1994, Mital 1995, Avila 1997) has shown that nitrogen fertilization can significantly increase basal area or volume growth. Larger trees in a stand showed greater diameter growth response to nitrogen fertilization than smaller trees, and individual trees in low-density stands exhibited more fertilization response than those growing in high-density stands (Shafii et al. 1990). Furthermore, rock type proved to be an important factor affecting stand-level growth response to N fertilization (Mika et al. 1992, Mital 1995), as well as the pattern of individual tree growth response within a stand (Shen et al. 2000). Forest habitat type (Daubenmire and Daubenmire 1968) and rock type are now used to guide operational fertilization programs in the region (Moore et al. 1998). However, there are no published individual tree mortality models that relate the probability of mortality to nitrogen fertilizer treatment, rock type, stand attributes, and tree attributes and that are compatible with growth simulation models, such as FVS (Wykoff et al. 1982), used in the region.

Informed forest management decisions need accurate growth and yield models that provide reliable growth information. A typical growth and yield model usually includes three components: survivor growth, ingrowth, and mortality. Mortality is the most difficult of these components to predict accurately. The causes for tree mortality are complicated and the key for a tree's survival is its genetic makeup and its environment (Spurr and Barnes 1980, Monserud and Rehfledt 1990). Lee (1971) distinguished between regular and irregular tree mortality. Regular mortality can be defined as the mortality due to competition for scarce resources, or due to tree age, insects, and diseases at endemic levels. On the other hand, irregular mortality is caused by some catastrophic event, for instance, fire, windthrow, or epidemic insect levels. These two classes of tree mortality may not always be independent of each other (Dobbertin and Biging 1998). This situation causes many growth and yield models to have large variability associated with their predictions; furthermore, the contribution to total variability due to the mortality component increases as the projection period increases (Gertner 1989). In our study, only regular tree mortality was considered.

Current mortality-modeling approaches can be grouped into two categories: classical statistical methods and computer-intensive statistical methods. For classical statistical methods, parameters of a flexible non-linear function bound by 0 and 1 are estimated using a maximum likelihood estimation procedure or other procedures. The probability of a tree dying within the next growing period, given the individual tree and stand characteristics, is computed in terms of this function. Conceptually, any nonlinear function (eg. a cumulative distribution function), which is implicitly defined on the range of 0 to 1, can be used to model individual tree mortality. However, only a few functions have been used to model individual tree mortality. These functions include the negative exponential function (Moser 1972), the logistic function

(Hamilton 1974), the normal or probit function (Monserud 1976), the Weibull function (Somer et al. 1980), the Richard's function (Buford and Hafley 1985), the gamma function (Kobe and Coates 1997). Of these functions, the logistic function is the most widely employed (Hamilton 1974, 1980, 1986, 1990, Hamilton and Wendt 1975, Hamilton and Edwards 1976, Monserud 1976, Buchman 1979, Buchman et al. 1983, Hann 1980, Lowell and Mitchell 1987, Vanclay 1991a, 1991b, 1995, Avila and Burkhart 1992, Zhang et al. 1997, Monserud and Sterba 1999). Its widespread application is probably due to its biologically preferable shape (Hamilton and Edwards 1976).

Two computer-intensive statistical methods: classification and regression trees (CART) (Breiman et al. 1984) and neural networks (Hertz et al. 1991) have been used to model individual tree mortality. In classification trees, a decision tree classifier recursively partitions the space of explanatory variables into locally constant regions, often hypercubes parallel to the variables' axes. There are many different schemes for estimating trees. The basic idea is to recursively choose a variable or combination of variables and to split the variable's space on a carefully chosen value. These schemes differ in allowing multiway splits or restricting binary splits and in deciding how the best split is computed. Classification trees have been increasingly applied to model individual tree mortality (Verbyla 1987, Byler et al. 1990, LeMay 1995, Dobbertin and Biging 1998). In neural networks, supervised feed-forward single hidden layer neural networks with a logistic output activation function are very general and have been shown by many authors that any continuous function can be approximated by these networks for sufficiently large numbers of hidden units. Such networks have been used to model individual tree mortality (Guan and Gertner 1991b, 1995). Guan and Gertner (1991a) built a two hidden-layered neural network with a logistic output activation function to model individual tree mortality. Neither

classification trees nor neural networks have led to significant improvement in our ability to predict mortality over analyzes that use logistic regression methods (Hasenauer and Merkl 1997, Monserud and Sterba 1999). Furthermore, tests of hypotheses can not be performed easily based on computer-intensive statistical mortality models. Therefore, the logistic function was chosen to model individual tree mortality in this study since our primary objective was to develop an individual tree mortality model and assess the effect of nitrogen fertilization and rock type on tree mortality.

### Data

Data used in this study was obtained from Intermountain Forest Tree Nutrition Cooperative (IFTNC) study sites. The study area includes six geographic regions: northern Idaho, western Montana, central Idaho, northeast Oregon, central Washington, and northeast Washington. From 1980 to 1982, the IFTNC established a total of 94 fertilizer trials (installations) throughout the six regions.

Installations were located in second-growth, even-aged, managed Douglas-fir stands. Most stands had been thinned 5 to12 years prior to plot establishment; a few stands were unthinned, but naturally well spaced. Stands were selected to represent a range of stand density, tree age and size, and site productivity. The stands were dominated by Douglas-fir and only Douglas-fir tree mortality was modeled.

Each installation contained six square plots ranging from 0.04 to 0.08 ha in size. The plot size was determined based on average tree size and stand density so that each plot contained at least ten Douglas-fir sample trees. The plots were selected to minimize between-plot variation in terrain, vegetation composition, tree stocking, and tree size at a site. Plots were grouped into two

blocks of three plots based on similarity of these features to further reduce variation. Three fertilizer treatments — 0, 224, and 448 kg/ha of nitrogen — were randomly assigned to the plots within each block. Nitrogen in the form of urea was applied in the late fall utilizing handheld spreaders.

All live trees were measured for height (to the nearest 0.03 m) and diameter (to the nearest 0.025 cm) at the initiation of the experiment. Every plot was revisited six years after experiment establishment, and any incidence of tree mortality along with probable cause was noted. A total of 12590 Douglas-fir trees, of which 12145 trees were classified as live and 445 (3.53%) were classified as dead, located on 564 plots across 94 installations, were used in this analysis. Thus, each tree was observed over a 6-year period. Habitat was determined on site for each plot and each plot was assigned to one of five habitat type categories: grand fir (Abies grandis), dry Douglas-fir (Pseudotsuga menziesii), moist Douglas-fir, western redcedar (Thuja *Plicata*), and western hemlock (*Tsuga heterophylla*). Since there were limited observations within selected habitat types on some rock types, in our analysis, habitat type was specified at two levels. The moist level included grand fir, moist Douglas-fir, western redcedar, and western hemlock habitat types and the dry level included dry Douglas-fir habitat types. Moist Douglas-fir types occur in a region of north central Washington where grand fir is completely absent in its geographic distribution. Thus, there can be no sites classified as grand fir habitat types in this geographic sub-region (Williams and Lillybridge 1983). The moist Douglas-fir sites in our study are similar to grand fir types elsewhere and we included them in the moist site category in our analysis. Rock samples were collected at each location and, after examination by a geologist, each installation was assigned to one of five rock type categories: granite, basalt, meta-sediment, sediment, and mixed --- glacial till. Individual tree records were checked for species codes,

diameter at breast height, crown class codes, condition codes, crown ratio, and height, and individual plot records were compiled for habitat type codes, rock type codes, treatment codes, slope, aspect, elevation, stand age, and Douglas-fir site index (Monserud 1984). Selected Douglas-fir stand and tree attributes are summarized in Table 1. In order to test the mortality model on an independent data set, the data set was randomly split into two data sets. Two-thirds of the data, a total of 8394 Douglas-fir trees of which 295 (3.51%) trees were classified as dead, were used as the estimation data and the other one third of the data, a total of 4196 Douglas-fir trees of which 150 (3.57%) tress were classified as dead, were used as the validation data.

## Analysis

## Mortality Model

Model development in our study was based on both biological and statistical considerations. The SAS PROC LOGISTIC procedure (SAS Institute 1989), which fits the linear logistic regression model for binary data by the method of maximum likelihood, was used to model individual tree mortality as a logistic function of site, tree size, and competition following the biological rationale of Monserud and Sterba (1999).

$$P = \frac{1}{1 + \exp(-(b_0 + SITE + SIZE + COMP))}$$
(1)

where:

*P* = 6-year probability of tree mortality

$$SITE = \sum_{k=1}^{4} b_{1k} RC_k + \sum_{i=1}^{2} b_{2i} TT_i$$
(2)

$$SIZE = b_3 DBH/100 \tag{3}$$

$$COMP = b_{4} CR + b_{5} TPH/1000 + b_{6} BAL/BA$$
(4)

 $RC_k$  = a set of dummy variables for the 5 rock types

 $(RC_1 \text{ was coded } 1 \text{ on granite rocks and } 0 \text{ otherwise,}$ 

 $RC_2$  was coded 1 on basalt rocks and 0 otherwise,

 $RC_3$  was coded 1 on meta-sedimentary rocks and 0 otherwise, and

 $RC_4$  was coded 1 on sedimentary rocks and 0 otherwise.)

 $TT_t$  = a set of variables for the 3 treatment types

(TT<sub>1</sub> was coded 1 with the 224 kg N/ha treatment and 0 otherwise, and

 $TT_2$  was coded 1 with the 448 kg N/ha treatment and 0 otherwise)

DBH = tree diameter at breast height (cm)

*CR* = tree crown ratio

*TPH* = number of trees per ha (trees/ha)

BAL = basal area in trees larger than the subject tree (m<sup>2</sup>/ha) (Wykoff et al. 1982,
 Wykoff 1990)

BA = basal area per ha (m<sup>2</sup>/ha)

 $b_{11}, b_{12}, b_{13}, b_{14}, b_{21}, b_{22}, b_3, b_4, b_5, b_6$  = parameters to be estimated

In the combined site effect (eq. 2). because rock type has been shown to be an important factor affecting stand-level growth response to N fertilization (Moore et al. 1998) and could represent differences in the forest nutritional environment (Shen et al. 2000), a set of dummy variables *RC* representing rock effects were added to Monserud and Sterba's (1999) original individual tree mortality model. Fertilizer treatment can raise site productivity by adding readily

and

available sources of nutrients to increase a site's nutrient capital. Thus, a set of dummy variables *TT* representing treatment effects was added to the mortality model.

Habitat type is a land classification based on expected climax vegetation (Daubenmire and Daubenmire 1968) and could represent a variety of moisture regimes. Interestingly when the moist habitat type alone stayed in the model, the coefficient associated with the moist habitat type had a positive sign, indicating that the probability of tree mortality on moist sites is higher than on dry sites. This is illogical biologically. Habitat type became insignificant when the number of trees per ha (*TPH*) was added to the model. Thus, habitat type was not included in the mortality model. Other site-specific variables were not considered in our analysis to avoid overfitting the resulting mortality model.

In the size effect (eq. 3), diameter at breast height (*DBH*) is an important and reliable measure of a tree's size. Generally, the larger the tree, the greater its chances of competing for scarce resources, indicating the probability of mortality decreases with increasing *DBH*. Thus, many mortality models include this variable (eg. Monserud 1976, Buchman et al. 1983, Vanclay 1991a, McTague and Stansfield 1994, Monserud and Sterba 1999). Two transformations of *DBH*: 1/*DBH* and *DBH*<sup>2</sup> are useful to represent the nonlinear size effect. The 1/*DBH* term allows the mortality model to estimate accurately the large mortality rates for small trees (Hamilton 1986). The *DBH*<sup>2</sup> term allows the mortality model to represent the increased mortality rates for the largest and oldest trees, i.e., the senescence effect (Buchman 1983, Harcombe 1987, Monserud and Sterba 1999). However, both transformations were not included in the mortality model since they were insignificant in the presence of *DBH*.

In the combined competition effect (eq. 4), tree crown ratio (CR) is a measure of foliage quantity indicative of tree vigor and is thus an important factor affecting the probability of

mortality. Usually, mortality rates decrease with increasing CR. Many mortality models include this variable (eg. Avila and Burkhart 1992, Zhang et al. 1997, Monserud and Sterba 1999). Although greatly dependent on tree vigor, the probability of a tree dying within the next growing period is also conditioned by competition with other trees for scarce resources. Overall stand density effects were represented in the mortality model by the number of trees per ha (TPH) rather than the square root of basal area,  $BA^{0.5}$  (Hamilton 1986), because inclusion of TPH in place of BA<sup>0.5</sup> resulted in an decrease of 32.9 in the Akaike Information Criterion (AIC), (Akaike 1974), and an decrease of 32.9 in the Schwarz Bayesian Information Criterion (SBIC), (Schwarz 1978). Furthermore, the probability of a tree dying within the next growing period is also dependent on its competitive status relative to neighboring trees. The BAL/BA term (Vanclay 1991a), equivalently 1-PCT (Stage 1973) where PCT is tree's percentile in the stand basal area distribution, was included in the mortality model in place of BAL (Monserud and Sterba 1999) because inclusion of BAL/BA resulted in an decrease of 4.8 in AIC and an decrease of 4.8 in SBIC. Relative rank (BAL/BA) allows the effect of relative size to vary with changes in basal area. Since no interaction terms were found to be significant for this particular data set, only main effects were included in the mortality model.

#### Model Evaluation

Examining the performance of the mortality model on the fit data set and testing the model on the independent validation data set comprised model evaluation. Logistics models can be used to produce stochastic or deterministic predictions of mortality. When regression predictions are stochastically applied, the predicted probability of a tree dying within the next growing period is compared with a random number generated from a uniform distribution with

the open interval 0 to 1. The tree is assigned to the predicted mortality class if the random number is less than the predicted probability of mortality. Deterministic predictions can be made in two different ways. The first way is to produce the number of dead trees per ha each sample tree represents by multiplying the per-hectare expansion factor by the tree's predicted probability of mortality. This method gives the expected values for the stochastic method in any given time period (Weber et al. 1986). The second way is to convert the logistic probability model predictions into dichotomous events (i.e., survival and mortality) predictions by using a threshold. The tree is assigned to the predicted mortality class if the predicted probability of mortality exceeds the threshold. We used both methods.

## Fertilizer Treatment Effect and Rock Type Effect

Three hypotheses: (1) there are no differences among the control and fertilized plots, (2) there is no difference between plots with the application of 224 kg N/ha and plots with the application of 448 kg N/ha, and (3) there are no differences among rock types which were tested separately based on the mortality model (eq. 1). The generalized likelihood ratio test (GLRT) method (Bain and Engelhardt 1991) was used to test these hypotheses.

#### Fertilization response estimation

To quantify an individual tree's response to nitrogen fertilization, the response ratio (R) for annual probability of mortality is defined as

$$R_{t} = \frac{1 - (1 - \hat{P}_{t})^{\frac{1}{6}}}{1 - (1 - \hat{P}_{0})^{\frac{1}{6}}}, t = 1 \text{ or } 2$$
(5)

where:

- $R_1$  = response ratio for the 224 kg N/ha treatment
- $R_2$  = response ratio for the 448 kg N/ha treatment
- $P_1$  = predicted value from the mortality model (eq. 1) with the 224 kg N/ha treatment
- $P_2$  = predicted value from the mortality model (eq. 1) with the 448 kg N/ha treatment
- $P_0$  = predicted value from the mortality model (eq. 1) with no treatment

Like a multiplier (Hamilton 1994), R measures relative mortality response to fertilization compared to a no-treatment alternative. When R is equal to 1, annual probability of mortality remains unchanged with the application of nitrogen fertilizer; when R is greater than 1, annual probability of mortality increases due to nitrogen fertilization; when R is less than 1, annual probability of mortality decreases due to nitrogen fertilization. However, it should be noted that higher relative response does not necessarily translate into higher absolute probability of mortality. Absolute probability of mortality depends on R and probability of mortality under the no-treatment alternative as well.

## Results

The maximum-likelihood estimates of the parameters, standard errors, Wald Chi-Square statistics, and p-values of the parameters. from the SAS PROC LOGISTIC procedure, for the mortality model (eq.1) are listed in Table 2. All coefficients associated with continuous variables are statistically significant at  $\alpha = 0.05$ . The coefficients of *DBH* and *CR* are negative, indicating that the probability of mortality will be less as tree diameter and crown ratio increase, respectively. The coefficients of *TPH* and *BAL/BA* are positive indicating that the probability of mortality will be higher as overall stand density and basal area in larger trees increase. Those

changes suggest a tree's competitive status is less favorable in the stand. The Wald Chi-Square Statistics in Table 2 show that of continuous variables, the most important variable is crown ratio CR; the second most important is number of trees per ha TPH; the third most important is diameter DBH; and the fourth most important predictor is relative rank BAL/BA.

Predicted and observed mortality rates with respect to rock type, treatment, diameter class, crown ratio, number of trees per ha, and relative rank (*BAL/BA*) for the fit data set are examined in Figure 1. The predictions perfectly matched the observed mortality rates for all rock types and all treatments. The predictions were close to the observed mortality rates across all diameter classes. The model slightly overestimated the mortality rates in the 0-0.2 and 0.4-0.6 *CR* classes and slightly underestimated the mortality rates in the 0.2-0.4 *CR* class. This lack of a consistent error demonstrates that the model was well-behaved with respect to crown ratio. The predictions were close to the observed mortality rates *TPH* class. We further examined the model and found that predictions in the 1700-1850 trees/ha *TPH* class perfectly matched the observed mortality rates only in the 1700 trees/ha and above *TPH* class (10.3% observed vs. 14.4% predicted mortality rates). This lack of a consistent error indicated that the model well with respect to number of trees per ha. Predicted vs. observed mortality rates with respect to relative rank (*BAL/BA*) were in close agreement.

We also validated the model by simulating mortality using a threshold value. We sorted the estimated probabilities of mortality from the logistic mortality model (eq.1) for the trees in the fit data set and used as the threshold value the predicted probability (0.1891) of mortality for the tree at the 96.49 (100-3.51[the average observed mortality rate]) percentile point. Using this

validation procedure, the model correctly classified 97.4% of the live trees and 27.5% of the dead trees.

We compared our model predictions with observed mortality rates in the validation data set. The predicted 6-year mortality (3.65%) is only slightly higher than observed (3.51%). We also compared observed with predicted 6-year mortality rates with respect to rock type, treatment, diameter class, crown ratio, number of tree per ha, and relative rank (*BAL/BA*) in Figure 2. In general, predictions are close to the observed mortality rates, with no detectable trend. Mortality is somewhat overestimated in the smallest diameter class, the smallest crown ratios (CR < 0.2), and the densest stands (TPH > 1700 trees/ha). The same threshold value of 0.1891 was also used to simulate mortality in the test data set. In the test data set this procedure correctly classified 97.0% of the live trees and 28.0% of the dead trees.

The "GLRT Chi-Square" value of 36.080 is statistically significant, for the null hypothesis that there are no differences among the control and fertilized plots with two degrees of freedom, indicating that nitrogen fertilization will increase the mortality rate as shown in Table 2. The "GLRT Chi-Square" value of 10.878 is statistically significant, for the null hypothesis that there is no difference between plots with the application of 224 kg N/ha and plots with the application of 448 kg N/ha with one degree of freedom, indicating that the mortality rate will increase as the nitrogen application rate increases as shown in Table 2. The "GLRT Chi-Square" value of 87.982 is statistically significant, for the null hypothesis that there are no differences among rock types with four degrees of freedom, indicating that the effect of rock type on mortality rate is significant. Of the coefficients associated with rock types shown in Table 2, the coefficient of sedimentary rocks is the smallest, resulting in the lowest mortality rate on sedimentary rocks. The coefficient of meta-sedimentary rocks is the largest, resulting in the

highest mortality rate on meta-sedimentary rocks. The coefficients of granite and basalt rocks are insignificant, indicating that the effect of granite and basalt rocks on mortality rate is similar to that of mixed rocks.

The average Douglas-fir plot fertilization response ratios R for annual mortality rate by rock type and treatment based on the mortality model (eq. 1 and eq. 5) and the fit data set are provided in Table 3. The 448 kg N/ha treatment produced greater relative response than 224 kg N/ha treatment. For each combination of treatments and rock types, the result from a *t* test conducted based on the number of plots involved reveals that all responses were significantly different than the null hypothesis that R = 1 at  $\alpha = 0.01$ .

#### Discussion

The results of this study are directly useful for qualifying nitrogen fertilizer response of individual Douglas-fir trees in the region. Equation 1 is compatible with individual tree growth simulation models, such as Forest Vegetation Simulator (i.e. FVS, Wykoff et al. 1982), widely used to forecast growth and yield in the inland Northwest. Alternatively, the parameters provided in Table 3 could be used as crude individual tree N fertilization response mortality rate multipliers by those who do not use individual tree simulation models formulated similar to the FVS model.

Interestingly, when the moist habitat type alone stayed in the mortality model, the coefficient associated with the moist habitat type had a positive sign, indicating that the probability of tree mortality on moist sites is higher than on dry sites. This is counterintuitive, and we feel different stand densities on these two habitats induced this phenomenon. On average, there were 733 trees/ha on moist sites and 586 trees/ha on dry sites. Therefore in our data set

(and in many others) density and habitat type are confounded since many more trees naturally become established and subsequently persist throughout stand development. Furthermore, foresters maintain higher densities on better sites during intermediate stand density management treatments. We did not include habitat type in the predictive model.

The quantitative insights into the relationships between individual tree mortality and competition across a variety of mineral nutrient (i.e. rock type) environments were developed by evaluating the individual tree mortality (eq. 1) and the response ratio (eq. 5) for three treatment levels (control, 224 kg N/ha, and 448 kg N/ha) and five rock types (granite, basalt, meta-sedimentary, sedimentary, and mixed) across a range of tree diameters from 6 to78 cm, and *BAL/BA* from 0 to 1 with the values of other independent variables being held constant at their means.

As expected, suppressed trees (i.e. those of small diameter with high *BAL/BA*) showed higher probability of mortality over a 6-year period than did dominant trees (i.e. those of large diameter with low *BAL/BA*) growing in the same stand (Figure 3). Two interesting features were revealed in Figure 3. The first is associated with the shapes of the mortality surfaces across a variety of mineral nutrient environments. The granite and meta-sedimentary rocks tend to weather to sandy soils, with low cation-exchange holding capacities (Buol et al. 1989). Thus, the inter-tree competition for scarce resources is acute, resulting in the obviously upward-sloping shape of the mortality surface for granite and meta-sedimentary rocks. Soils derived from basaltic and mixed rocks, on the other hand, have a clayey texture with a high nutrient holding capacity. As a result, the inter-tree competition for scarce resources is less, resulting in the slightly upward-sloping shape of the mortality surface for basaltic and mixed rocks. Sedimentary soils tend to be richer in clay minerals and have a higher nutrient holding capacity. Thus, the

mortality due to competition for resources is very low, resulting in the nearly flat shape of the mortality surface for sedimentary rocks. We propose that lower K availability on granite and meta-sedimentary rocks explains the higher mortality rates on unfertilized plots for these rock types. Mika and Moore (1991) showed that sites with low foliar K levels prior to fertilization incurred substantially higher stand level mortality than those sites with adequate foliar K. The work of Shaw et al. (1998) suggests a biological explanation for these results. They found that Douglas-fir seedlings grown in a low K environment had significantly lower phenolic and tannin concentrations and lower ratios of these compounds to sugars in their roots than did seedlings with high K supplied. Further, Entry et al. (1991) demonstrated that low root phenol/sugar ratios were associated with higher incidence of *Armillaria* infection. Our results indicate that rock type represents broad differences in the nutrient environment where trees grow. We suggest that rock type, or a conceptually similar characteristic. should be useful for explaining variation in individual tree mortality in other geographic regions.

The second interesting feature is associated with the shapes of the mortality surfaces associated with the different nitrogen application rates. The degree of upward-sloping for the mortality surface increases with increasing the nitrogen application rate. This indicates that nitrogen fertilization changes individual tree mortality. with higher probabilities of mortality associated with heavier nitrogen application. We feel there are three plausible reasons. First, nitrogen fertilization increases individual tree growth. As trees become larger, fewer trees can be supported per hectare. Thus, an acceleration of growth due to nitrogen fertilization can produce dense stands, resulting in increasing competition and mortality (Binkley 1986). Second, nitrogen only fertilization may create nutrient imbalances, and thus create nutrient stress, such as for K discussed above, and therefore increase mortality (Binkley 1986). Adding other limiting

nutrients in the fertilizer blend may reduce mortality levels observed in our study. Third, nitrogen fertilization may decrease the resistance of trees to wind, snow, and pathogens such as root rot (Mika and Vander Ploeg 1991, Mika et al. 1992). Thus, the mortality due to wind, snow, and root rot increases as the nitrogen application rate increases.

The response ratios (eq. 5) for annual probability of tree mortality across a range of tree diameters for all rock types for each fertilizer treatment are almost identical (Table 3). However, the average response ratio of the 448 kg N treatment (about 2.50) is much greater than that of the 224 kg N treatment (about 1.54).

#### Conclusions

This study quantifies the effect of rock type and nitrogen fertilization on tree mortality. Trees growing on soils developed from granite and meta-sedimentary rocks exhibited greater probabilities of mortality than did those growing on other rocks. The probabilities of mortality for trees growing on sedimentary rocks were very low. The probabilities of tree mortality increased with increasing nitrogen fertilizer application rates. Furthermore, the response ratios were nearly constant (about 1.54) across a range of tree diameters for all rock types with the 224 kg N treatment. The response ratios were also nearly constant (about 2.50) across a range of tree diameters for all rock types with the 448 kg N treatment. Therefore, our study quantitatively demonstrates differences in tree mortality across broad differences in the nutrient environment represented by different rock types. The mortality equations were formulated to be compatible with individual tree distance independent simulation models. Incorporating these new equations into growth and yield simulators. such as FVS, would provide better representation of nitrogen fertilization effects on tree mortality and resultant stand development dynamics.

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24

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Table 1. Summary statistics of selected Douglas-fir stand and tree attributes at the beginning of the 6-year growth period.

Attribute	Mean	SD	Minimum	Maximum
Site index* (m @ 50 yr)	19.2	3.2	13.1	27.7
Age (yr)	65	17	27	100
Number of trees (trees/ha)	658	308	210	2002
Mean tree height (m)	18.9	3.8	8.7	31.2
Top height (m)	20.4	4.3	8.9	36.9
Basal area (m <sup>2</sup> /ha)	32.3	10.6	7.3	77.0
Crown competition factor**	157	48	45	329
Quadratic mean diameter (cm)	26.14	5.92	13.26	49.00
Diameter at breast height (cm)	24.15	8.94	5.89	77.27
Total height (m)	18.4	5.0	4.5	40.5
Crown ratio	0.45	0.14	0.10	0.99

\* Monserud (1984).

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\*\* Wykoff et al. (1982).

Variable	Estimate	Std error	Wald Chi-Square	P > Chi-Square
Constant	-3.1157	0.9062	11.8216	0.0006
RCI	0.3313	0.1962	2.8508	0.0913
RC <sub>2</sub>	-0.2605	0.1853	1.9767	0.1597
RC3	0.8164	0.1716	22.6219	0.0001
RC₄	-2.3389	0.5964	15.3785	0.0001
$TT_{I}$	0.4382	0.1721	6.4875	0.0109
TT <sub>2</sub>	0.9220	0.1593	33.5130	0.0001
<i>DBH</i> /100	-4.5682	1.8703	5.9659	0.0146
CR	-4.6037	0.5542	69.0180	0.0001
<i>TPH</i> /1000	1.1847	0.1979	35.8542	0.0001
BAL/BA	1.1708	0.5345	4.7976	0.0285

Table 2. Parameter estimates for the mortality model (eq. 1) using the maximum likelihood estimation method.

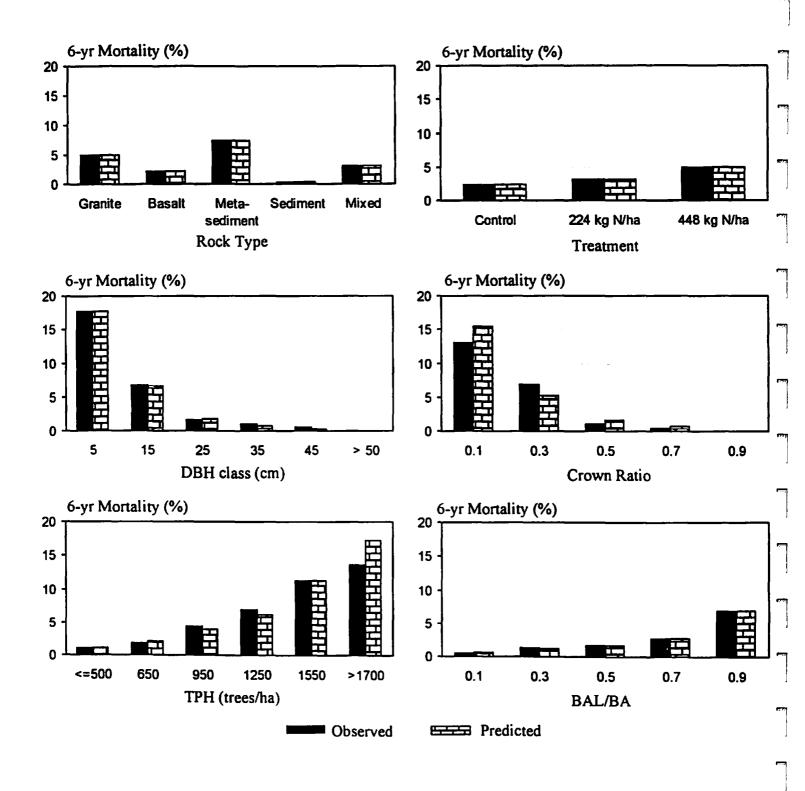
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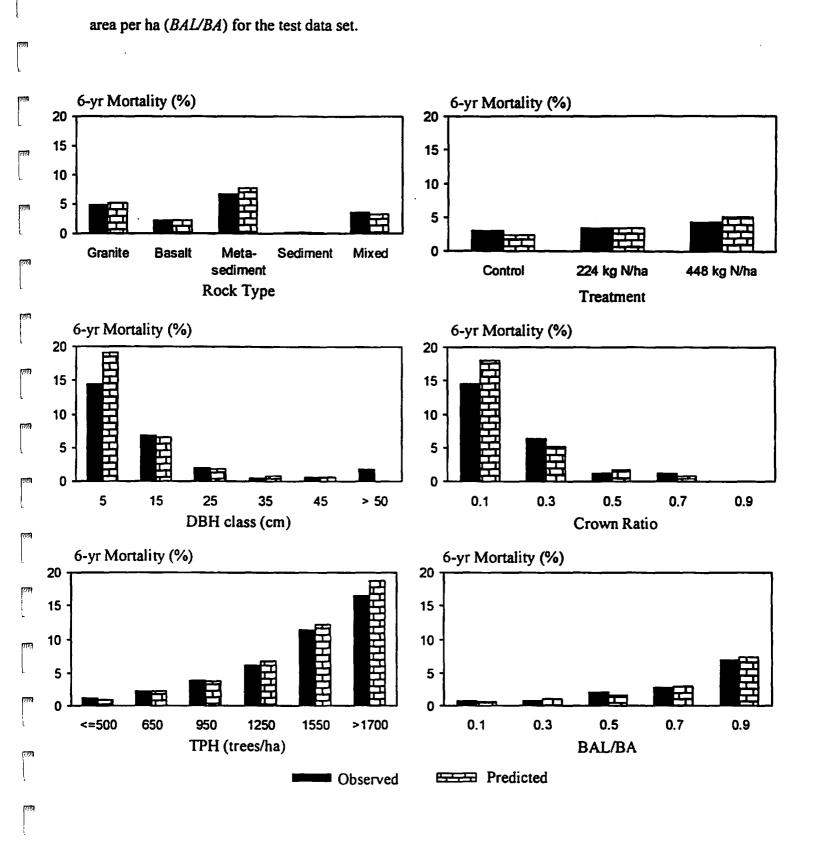
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Table 3. Average plot response ratios R for annual mortality rate by rock type and treatment based on the mortality model (eq. 1).

Treatment			
224 kg N/ha	448 kg N/ha		
1.53250	2.44120		
1.54076	2.47469		
1.51931	2.38890		
1.54913	2.50927		
1.53693	2.45867		
	224 kg N/ha 1.53250 1.54076 1.51931 1.54913		

area per ha (BAL/BA) for the fit data set.





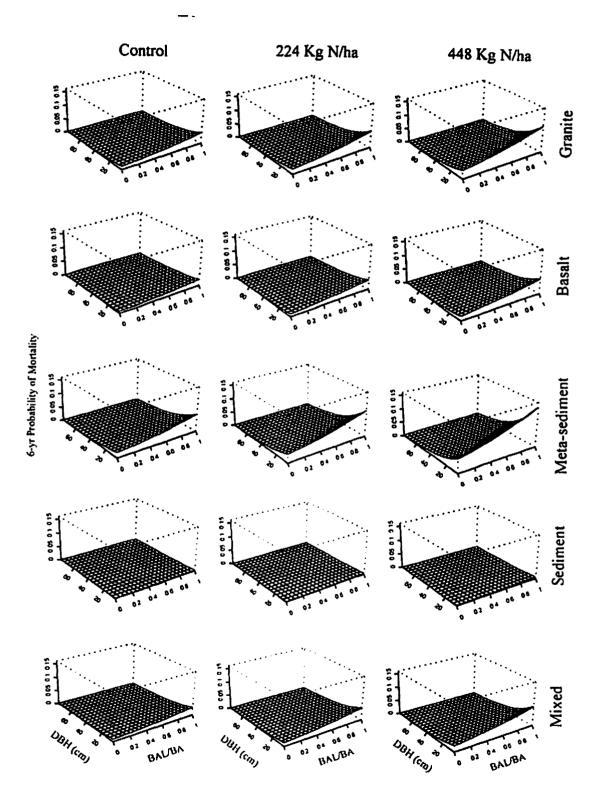


Figure 3. Six-year probability of tree mortality (eq. 1) by tree diameter (DBH) and basal area in larger trees over basal area per ha (BAL/BA) for five rock types and three treatments.