# Modify FOFEM for use in the Coastal Plain Region of the Southeastern US

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G. Geoff Wang[1]
Steve Wangen[1]
Elizabeth Reinhardt[2]
Thomas A. Waldrop[3]
Kenneth W. Outcalt[3]
Joan L. Walker[3]
Dale G. Brockway[3]
James D. Haywood[3]
J. Kevin Hiers[4]

[1]Clemson University
[2]USDA Forest Service, RMRS
[3]USDA Forest Service, SRS
[4]Joseph W. Jones Ecological Research Center

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# Executive Summary

Millions of acres of pine dominated forests are burned each year in the Coastal Plain region of the Southeastern US. Many prescribed fires in the southeast are conducted to restore or maintain longleaf pine forests, once a dominant feature in the Southeast but now only occupying less than 5% of their pre-settlement extent. In order to effectively conduct prescribed burning in longleaf pine forests while leaving the overstory intact (i.e., minimizing fire-induced mortality of canopy trees), we must be able to predict how longleaf pine trees would respond across a gradient of burning conditions. To better plan for fire effects, predictive models such as FOFEM (First Order Fire Effects Model) are needed. Currently, FOFEM has been used by thousands of fire and land managers across the United States. It synthesizes the results of many empirical fire effects studies into one computer program that can be easily and quickly used by novice and expert resource managers. However, most empirical models within FOFEM have been developed exclusively based on data from western conifer forests. It is commonly acknowledged that empirical models lack generality and cannot be applied beyond the specific conditions on which they are based. Our study modified FOFEM for use in the Coastal Plain region of the Southeastern US. Specifically, we compiled data from published and unpublished fire studies and used these compiled data to recalibrate the existing models or to develop new models for use in FOFEM.

We developed the following regression equation to predict bark thickness at breast height (*BT*) from diameter at breast height (dbh):

$$BT = 0.435 + 0.031 * dbh$$

The equation currently used in FOFEM to predict longleaf pine bark thickness does not include a constant term. Exclusion of a constant term from regression model forces regression line to go through the origin, which resulted in prediction bias based on our data.

We developed several tree mortality models. Using the same variables currently used in the FOFEM, we developed the following tree mortality model:

$$p(mortality) = \frac{1}{1 + e^{-1.507 + 4.450\,SCH - 4.309\,SCH^2 + 12.788\,BT}}$$

Where SCH = Proportion of crown scorched (0-1); BT = Bark Thickness (cm).

Based on all variables available in our compiled data, we developed the following two tree mortality models:

$$p(mortality) = \frac{1}{1 + e^{-2.191 + 6.482\,RH^2 + 30.076\,BT^2}}$$

$$p(mortality) = \frac{1}{1 + e^{-2.427 + 5.512\,SCH - 5.228\,SCH^2 + 6.099\,RH^2 + 31.805\,BT^2}}$$

Where SCH = Proportion of crown scorched (0-1); BT = Bark Thickness (cm); RH = Relative Humidity (0-1).

Based on pre- and post-fire destructive sampling of forest floor, we have developed the following model for predicting forest floor consumption:

$$Y = -3.893 + 0.944*X_1 - 0.078*X_2$$

Where Y = forest floor consumption (Mg/ha), $X_1$ = forest floor amount before burn (Mg/ha), and $X_2$ = forest floor moisture content (% based on dry weight).

Based on Brown's fuel transect measurements, we have also developed the following equation for predicting forest floor depth removal:

$$Y = -9.939 + 0.896*X - 29.582/X$$

Where Y = forest floor depth removed (mm) and X = forest floor depth before burn (mm). Forest floor moisture content was not significant, and therefore not included in the equation.

Based on duff-pin measurements, we also found about 5% complete forest floor removal (therefore, with mineral soil exposed), and about 6.8% zero forest removal.

These recalibrated or newly developed models were then incorporated into the existing computer programs to create a new version of FOFEM for use in the longleaf pine forests in the Coastal Plain region of the Southeastern US. The modified version of FOFEM gives fire and land managers a useful and much needed tool for better planning and implementing future prescribed burning activities.

Two draft manuscripts are attached with this report. The first manuscript deals explicitly with the development of tree mortality models for longleaf pine trees during fires. It provides the best possible model for predicting fire-induced longleaf pine tree mortality, given the data compiled in our study. The second manuscript investigates the effects of fire on bark thickness of longleaf pine trees. This manuscript is an addition to our original proposal.

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## 1. Introduction

### 1.1. Prescribed Fires in the Southeast US

Fire plays a major ecological role in shaping vegetation of the Southeast US (Dale et al. 2000, Stanturf et al. 2002). For example, longleaf pine (*Pinus palustris* P. Mill.) forests in the Coastal Plain region owe their existence to frequent and low intensity fires. Effective fire suppression since 1930's coupled with previous resource exploitation has practically eliminated over 90% of longleaf pine forests that existed before the European settlement, threatening the diverse flora and fauna endemic to these forests. In order to restore ecological integrity and to reduce the high risk of uncharacteristically severe and destructive wildfires in these forests, prescribed burning programs have been initiated across the Southeastern US beginning in the 1950's. The extensive use of controlled fire to manage forests is well documented. For example, in the decade between 1985 and 1994, 4.1 million acres of pine-type forest are burned annually on federal, state and private land (Haines et al. 2001). To better plan for fire effects, forest resource managers need models to predict the consequences of implementing prescribed burning under different conditions. For example, computer models can be used in setting acceptable upper and lower fuel moistures for conducting prescribed burns, determining the number of acres that may be burned on a given day without exceeding particulate emission limits, and comparing expected outcomes of alternative actions.

Prescribed fire has been used as a management tool in the Southeastern US for millennia. In addition to routine prescribed burning implemented by federal, state and private landowners to achieve management objectives, there are many completed and ongoing research projects studying prescribed fire effects on forest ecosystems in the Coastal Plain region. These prescribed fires are aimed to promote regeneration of target tree species, encourage the development of the herbaceous layer, reduce fuel loading, and/or control competing vegetation. Despite the long history and extensive application of prescribed fires in the region, models for predicting fire effects have not been well developed and applied. Consequently, planners of prescribed fires largely rely on past experience or rule of thumb. There is an urgent need for the development and application of quantitative fire effect models in guiding ongoing prescribed burning activities to better achieve management and research objectives.

### 1.2. FOFEM – The First Order Fire Effect Models

Previously, the Joint Fire Science Program (JFSP) has supported the development of FOFEM (First Order Fire Effects Model) at the USDA Forest Service Fire Science Laboratory in Missoula, MT. FOFEM has been under development since 1998. It is a computer program that was developed to meet needs of resource managers, planners, and analysts in predicting and planning for fire effects. It has been used by thousands of fire and land managers across the United States in a spectrum of agencies. It has been endorsed by the National Wildfire Coordinating Group, and sponsored by the Washington Office Fire and Aviation Management. It is part of the curriculum of national interagency courses including Prescribed Fire Behavior Analyst, Technical Fire

Management, and Advanced Fire Effects, as well as regional fire effects and smoke courses. It is used for purposes including environmental assessment, fire severity assessment, fire and silvicultural prescription development, and preparation of timber salvage guidelines. FOFEM synthesizes the results of many empirical fire effects studies into one computer program that is easily and quickly used by novice and expert resource managers. It uses heuristic knowledge to bridge the gaps between empirical models and to select the most appropriate of alternative predictive procedures.

Currently, FOFEM (v5.2) provides quantitative fire effects predictions for tree mortality, fuel consumption, smoke production and soil heating from prescribed fires and wildfires. Although FOFEM takes a mechanistic approach to predict consumption of down woody fuels, emissions, and soil heating, it takes an empirical approach to predict tree mortality and consumption of litter, duff, and live vegetation fuels. Logistic regression models were used to predict probability of tree mortality based on flame length or scorch height, and tree species and size. Regression models were used to predict duff consumptions based on moisture content and pre-fire duff depth. Consumption of litter and live vegetation fuels were predicted by rule of thumb. Consumption of down woody fuels by size class, and the resultant fire intensity over time were predicted using the BURNUP model, a physical model of heat transfer and burning rate of woody fuel particles. Emissions (and emission rate) of PM10, PM2.5, CO, $CO_2$, and $CH_4$ are predicted using the modified BURNUP model. Separate estimates of flaming and smoldering consumption in each time step for each fuel component are made by assuming that flaming combustion cannot be sustained below an intensity of ~15 kW/m$^2$. Emission factors for particulate and chemical emission were applied to the fuel consumed in flaming and smoldering combustion assuming the values of combustion efficiencies of 0.95 for flaming and 0.75 for smoldering. Soil heating is predicted at a range of soil depths over time since ignition. The soil heating model has been set up so that heat resulting from predicted fuel consumption is used as the source of soil heating. If there is duff, the model assumes that duff is the source of the soil heat; if not, other fuels drive the soil heating model. In contrast to mechanistic models that can be universally applied, empirical models are limited only to the data used in model development.

Despite its intended national scope, most empirical models within FOFEM (V5.2) have been developed exclusively based on data from western conifer forests. It is commonly acknowledged that empirical models lack generality and cannot be applied beyond the specific conditions on which they are based (Dickinson and Johnson 2001). User feedbacks (e.g., Carl Schmidt, Pers. Comm.) and our own preliminary testing (unpublished data) indicated that FOFEM significantly over predicted tree mortality and the consumption of litter and 1-hour fuels and under predicted duff consumption when applied in the Southeastern US. Therefore, the applicability of FOFEM to forests in the Southeastern US needs to be further tested. To provide reliable and accurate predictions, most empirical models within FOFEM need to be recalibrated or redeveloped based on data obtained from the Southeastern US.

1.3. Tree Mortality Model

Tree mortality may be the most important fire effect that needs to be carefully planned when conducting a prescribed burn in longleaf pine forests. Tree mortality due to fire can be directly caused by three types of tissue damages: crown (foliage and bud), stem (cambium), and root. These damages are commonly measured by crown scorch volume, crown consumption volume, cambium condition, and fine root kill. These measures are closely related to fire behavior parameters such as ground char, bole char, bole scorch height, and crown scorch height. The three types of tissue damage can work individually or in combination to cause tree mortality (Dickinson and Johnson 2001). Measures of crown damage (scorching and/or consumption) are most commonly used in tree mortality models. These variables often have the greatest predictive power. However, it is possible for the crowns of mature trees to escape injury during low intensity burning (Peterson and Ryan 1986). These low intensity fires can result in stem (cambium) damage and/or the mortality of fine roots, especially when applied after a long period of fire exclusion. Both cambium and root damages, which are likely correlated, are difficult to examine and quantify. Bark thickness is often used as a surrogate to indicate the resistance of cambium to fire damage. Ground char (degree of duff consumption) may be the best surrogate of root damage.

In some cases, fire may not be lethal enough to cause direct mortality, but it may have substantially weakened the vitality of trees and predisposed them to biological (e.g., insect and pathogen) or environmental (e.g., drought) stresses. Separating effects of these confounding factors from direct fire effects in tree mortality is often difficult. However, it is likely that the contribution of direct fire effects to tree mortality would diminish over years since the burn. Consequently, there exists a window of time within which assessing fire-caused mortality is most adequate. Although Wyant et al. (1986) state that most long-term studies show fire-caused mortality peaks in the second growing season following the fire, most literature shows that preponderance of fire-caused mortality occurs in the first full post-fire growing season (Wade and Johansen 1986). In any case, confounding factors are often implicitly included in modeling tree mortality unless the cause of post-fire mortality is explicitly identified.

Given the same degree of fire damage to crown, stem, and/or root, tree mortality differs among species and changes with tree sizes. Differences in fire-resistance among species, due to their differences in crown characteristic, bark thickness and/or rooting depth, are well recognized (e.g., Ryan and Reinhardt 1988, Rigolot 2004). For a given species, fire-resistance generally increases with tree size. In fact, tree dbh is widely recognized as a factor in resistance to fire damage. Large trees are more resistant to fire damage because their crowns are elevated more above the ground, their bark is thicker, and their heat capacity is larger. Most existing models show decreasing mortality with increasing dbh. However, McHugh and Kolb (2003) found a U-shaped dbh-mortality distribution for ponderosa pine, suggesting higher mortality for both the smallest and the largest trees when compared to trees of intermediate size. Hiers et al. (2003) also found that duff fires tend to kill older, larger longleaf pine more often than smaller trees. High mortality of large trees is likely related either to aging thus reduced growth rate (Van Mantgem et al.

2003) or to deeper and drier duff buildup thus susceptible to smoldering fire (Miyanishi and Johnson 2002).

Because of differences in tree phenology/physiology and environmental conditions, fire season often significantly affect tree mortality. Growing season fires typically cause higher tree mortality when compared to dormant season fires (Robbins and Myers 1992). For example, Wade and Johansen (1986) stated that trees with near total foliage scorch but no crown consumption resulting from fires between October through March had a much higher likelihood of survival than those with similar damage caused by fires from April through September. In the Coastal Plain region, growing season fires have higher ambient temperature ($>30\ ^0$C) and generally light and variable wind, which increase the risk of crown damage (Robbins and Myers 1992). When burning during the dormant season, however, buds and branch cambium of southern pines can frequently survive complete crown scorch (Wade and Johansen 1986).

Even though mechanistic models are being developed to link fire behavior and tissue damage, little advancement has been made on drawing mechanistic links between patterns of tissue damage and tree death (Dickinson and Johnson 2001). Consequently, empirical models are commonly used in predicting tree mortality. Current models are typified by logistic regressions in which a continuous probability function is derived from binary tree mortality data (i.e., trees are either dead or alive at some time after fire). The equations have the following general from:

$$[1] \qquad P = \frac{1}{1 + e^{(b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_i x_i)}}$$

Where $P$ is the probability of tree death, the $x_i$'s are independent variables, and $b_i$'s are statistically derived coefficients. Generally, independent variables are descriptors or surrogates of fire behavior (e.g., fire-line intensity, flame length, char height) and fire effects (e.g., crown scorch, bark char, duff consumption). Use of fire behavior variables in the equation is obviously necessary when writing fire prescriptions and predicting mortality before the fire. After fire, direct tissue damage measurements may be more accurate (e.g., crown scorch height is less accurate than scorch volume). The best combinations of independent variables identified in some recent studies are: fine twig dieback, duration of temperature above $30\ ^0$C, depth of necrosis to bark thickness, and char (scorch) height (Yaussy et al. 2002); pre-fire growth rate and % crown scorch (Van Mantgem et al. 2003); total crown damaged (scorch plus consumption) and bole char severity (McHugh and Kolb 2003); measures of stem damage (Van Mantgem and Schwartz 2004); % crown scorch, depth of bark charring, and tree dbh (Rigolot 2004). It is suggested that the best combination of independent variables should include one measurement of tree size (e.g., dbh) and one measurement from each of the three types of tissue damages: crown, stem, and roots (Fowler and Hull Sieg 2004).

In FOFEM, tree mortality is computed using Model [1] fitted to data collected from western conifer trees greater than 5 inches dbh under-burned with prescribed fires (Ryan and Reinhardt 1988). Bark thickness and % crown volume scorched was selected as the

best predictors of tree mortality. Although several tree mortality studies have found their predictions to be robust and reasonably accurate, none of these studies was conducted using data obtained from the Southeastern US. In fact, FOFEM users found that tree mortality was significantly over predicted (Carl Schmidt, Pers. Comm.). The empirical nature of the model implies different coefficients may be needed for different sites and stands even the same independent variables remain as the best predictors. Furthermore, previous studies in the Southeastern US suggested that % crown scorch is a poor indicator of tree mortality (Wade and Johansen 1986, Outcalt and Foltz 2004). Complete crown scorch may not result in tree mortality of southern pines especially when prescribed fires are conducted during the dormant season. On the other hand, mortality of large longleaf pine trees was observed due to damage to cambium and fine roots by smoldering duff fires without any crown scorch (Hiers et al. 2003). Therefore new models with different predictors are likely needed.

1.4. Fuel Consumption

FOFEM predicts the consumption of the following fuel components: litter, duff, 0-1/4 inch, $\frac{1}{4}$ - 1 inch, 1-3 inch, 3 inch plus dead woody fuels (sound and rotten), herbaceous fuels, and shrub fuels. Consumption of all fuel components, except for dead woody fuels, is predicted using regression models or rules of thumb. It assumes 100% consumption of litter, which may be a reasonable assumption since most prescribed burns depend on litter to carry the fire. It assumes 100% consumption of the herbaceous fuels or 90% consumption if the cover type is a grass type and the season of burn is spring. In Southeastern US, for the pocosin cover type, in spring or winter shrub consumption is 90%, in summer or fall 80%. For non-pocosin types in the Southeastern US, shrub consumption is predicted according to Hough (1978). FOFEM does not predict whether a crown fire will occur and canopy fuels will be consumed.

Duff consumption has significant implications to tree regeneration and possible soil erosion. While other fuels are largely consumed by flaming combustion, smoldering combustion has been recognized as the major process by which duff is consumed. Smoldering combustion differs from flaming combustion in being a much slower, non-flaming oxidation of a porous char-forming solid. Three variables that control smoldering propagation in duff are moisture content, density and depth. A previous study suggested a positive relationship between fuel moisture content and minimum fuel depth required for smoldering propagation (Miyanishi and Johnson 2002). Therefore, moisture thresholds for duff consumption are likely depth-dependent. It was not surprising that, without considering duff depth, moisture thresholds were not found by Reinhardt et al. (1991). Two approaches to modeling duff consumption have been commonly used: (1) empirical regression models which correlate average duff consumption with various combinations of independent variables including indices of duff moisture, and (2) process-based models of radiative heat transfer from flaming front to the duff. In FOFEM, empirical regression models, taken from Brown et al. (1985), Harrington (1987), Hough (1978), and Reinhardt et al. (1991), were used to predict three aspects of duff consumption: duff depth reduction, % duff consumed, and mineral soil exposure.

Many empirical studies of duff consumption identified the same variables as important, including duff moisture content of the lower portion or the entire duff profile and its proxy such as thousand hour fuel moisture, pre-burn duff depth, and loading and consumption of woody fuels (e.g., Brown et al. 1985, Harrington 1987). Despite the consistency in the use of independent variables in the previous studies, difficulty was encountered in developing a single model for broad geographic ranges (Reinhardt et al. 1991). Region- and/or site-specific duff consumption regression models are likely needed for accurate prediction of duff consumption. As a result, FOFEM used models developed by Hough (1978) to estimate duff consumption for the Southeastern US. Although these models were the best available for southern pine communities in the Coastal Plain region at the time, Hough (1978) suggested the need for further improvement when new research findings become available.

## 2. Project Objectives

The objective of our study was to modify FOFEM for use in the longleaf pine forests in the Coastal Plain region of the Southeastern US. Specifically, we compiled data from published and unpublished prescribed fire studies and used these data to recalibrate the existing models or to develop new models for use in FOFEM. These recalibrated or newly developed models were then incorporated into the existing computer programs (FOFEM V5.2) to create a new version of FOFEM for use in the longleaf pine forests of the Coastal Plain region.

## 3. Materials and Methods

3.1. Study Area

Our study targeted longleaf pine (70) and longleaf – slash pine (83) cover types (Eyre 1980) in the Southeastern Plains, the Middle Atlantic Coastal Plain and the Southern Coastal Plain ecoregions of the Southeastern US, where numerous prescribed fire studies have generated an adequate database to achieve our objectives.

The Southeastern Plains have a mosaic of cropland, pasture, woodland, and forest. Natural vegetation was mostly longleaf pine forest consisting of a diversity of age classes, structure, and species in response to environmental gradients and natural disturbances. The Middle Atlantic Coastal Plain is found primarily in the Carolinas and other states to the north. Forest cover in the region, once dominated by longleaf pine in the Carolinas, is now dominated by loblolly pine (*P. taeda*). The Southern Coastal Plain extends from South Carolina and Georgia through much of central Florida, and along the Gulf coast lowlands of the Florida Panhandle, Alabama, and Mississippi. Natural vegetation included a variety of forest communities but dominated by longleaf-slash pine forests.

In the study area, frequent thunderstorms provide an ignition source for natural fires. In the past, Native Americans and European settlers also burned natural vegetation regularly. Regardless of ignition source, fire frequency and intensity have been dominant

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forces throughout the region on all but the wettest sites. Frequent light surface fires characterize most Coastal Plain ecosystems dominated by pines. The mid- to late 1900's represent a period of reduced fire frequency, size, and intensity, a shift that is a major source of change in the region's ecosystems, leading to increases in mesic species (that is, species adapted to moister conditions), increased understory stem density, increased woody cover in formerly open habitats, and decreases in fire-dependent species and ecosystems. As a result, prescribed fires become an essential management tool in restoring and maintaining many forest ecosystems in the region.

## 3.2. Data collection

We have conducted an extensive literature search to obtain data available in published fire effects studies. We also searched unpublished data (including ongoing studies that have not yet been published) through many personal contacts of our research team. To ensure compliance with the Data Quality Act, published data were limited to peer-reviewed sources and federal sources, and unpublished data were limited only to federal sources. Federal agencies (e.g., USFS) have their own Data Quality Control Protocols in place.  Most prescribed fires in the study area were set for operational and management purposes. Data used in the study were compiled from those prescribed fires conducted for research purposes, where the first order fire effects were often monitored.

Three datasets were compiled for the study. The first dataset (bark thickness dataset) was collected in the field ourselves. This data set was used to developed bark thickness model and to investigate the effect of fire on the bark thickness of longleaf pine trees. The second and the third datasets were compiled from complete and ongoing research projects conducted by various USFS scientists. The second dataset (tree mortality dataset) was used to develop of longleaf pine tree mortality models. The third dataset (fuel consumption dataset) was used to develop forest floor consumption models.

## 3.2.1. Bark thickness data

Bark thickness data was collected from the Escambia experimental Forest located near Brewton, Alabama.  Bark thickness was measured on 180 trees from stands subjected to different prescribed fire regime along the bole (0, 30, 60, 90, 140, and 200 centimeters from the ground) in each cardinal direction using a Haglof Barktax bark thickness gauge and estimated to the nearest 0.05 inch.  The four measurements at each height were averaged to account for variability in bark thickness. For each tree selected for bark thickness measurement, diameter at breast height (i.e., 140 cm aboveground; dbh) was also measured using a diameter tape. In total, we sampled 180 longleaf pine trees, with dbh ranged from 5 to 40 cm.

## 3.2.2. Tree mortality dataset

Data for the development of longleaf pine tree mortality models were assembled from three different locations: the Solon Dixon Forestry and Education center near Andalusia, Alabama, the Myakka River State Park near the gulf coast in middle peninsular Florida,

and the Escambia Experimental Forest located just outside of Brewton, Alabama.  The data from the Solon Dixon and Myakka sites are for individual fire events: a prescribed fire at Solon Dixon and an accidental fire at Myakka State Park.  The data from the Escambia Experimental forest is from an ongoing prescribed fire study, and data have been collected since the study's inception in 1973 (Boyer 2000).

Data sets from all sites were reduced to the maximum number of explanatory variables that were common to all sites.  Individual tree data from all sites included stem diameter measured at breast height (dbh, 1.4m), severity of crown scorch (% of live crown scorched), and tree status (live or dead) both before and at least one year after the sites had been burned.  In total there were 4968 individual tree observations recorded; 151 from the Myakka state park, 516 from Solon Dixon, and 4301 from Escambia.  Data collected for fire conditions included flame length, average rate of spread, average wind speed, season of burn (spring, summer, or winter), and average relative humidity (%) during the burn.

3.3.3 Fuel consumption dataset.

Fuel consumption dataset were collected on the Solon Dixon site, one of the National Fire and Fire Surrogate Study site in Alabama. Pre- and post-fire fuel data were collected following the methods from the National Fire and Fire Surrogate Study. A detailed description of the method is given by Waldrop et al. (2004).

Forest floor measurements were conducted in three different ways: destructive sampling, Brown's fuel transect method, and duff-pin method. Moisture content of forest floor and other fuel components were also determined for selective sampling points in destructive sampling (n = 87) and Brown's fuel transect method (n = 59). A large sample of duff-pin was implemented (n = 1607), and these data was used to calculate % mineral soil exposure. The fuel consumption dataset was provided to us by Dr. K.W. Outcalt.

3.3. Data analysis

Based on the bark thickness dataset, regression analyses were used to develop bark thickness models, which predicts bark thickness from diameter at breast height (dbh). Both regression models with and without a constant were used in our analyses. Regression without a constant was used in the FOFEM (v5.2) software. The newly developed models were compared to the model currently used in the FOFEM (v5.2) software. If significantly different, a newly developed model was then selected and incorporated into the modified FOFEM.

Based on the tree mortality dataset, longleaf pine tree mortality models were developed using logistic regression analyses. In addition to testing the model form currently used in the FOFEM (v5.2) software, various combinations of independent variables were also tested in order to find a best prediction model based on the data available. The resulting models were compared, based on both statistical and biological criteria, and the best

fitted models were selected (for details on model selection, see attached manuscript #1). These selected models were then incorporated into the modified FOFEM.

Based on the fuel consumption dataset, duff consumption models were developed using regression analyses to predict duff depth reduction, % duff consumed, and % mineral soil exposure. Various combinations of independent variables were tested based on the available data. These newly models were then incorporated into the modified FOFEM.

## 4. Results and Discussion

4.1. Bark Thickness Equations

The following regression equation was developed to predict bark thickness at breast height (*BT*) from dbh based on our data:

[2]     $BT = 0.048 * dbh$
         $P < 0.001, F_{1,179} = 934.949, R^2 = 0.965$

Our model was nearly identical to the equation currently used to predict longleaf pine bark thickness in the FOFEM (v5.2) software (*BT = 0.049 * DBH*, Duncan Lutes, pers. comm.). It appeared that no change would be needed in the modified FOFEM.

Most studies reported a close relationship between bark thickness and diameter, although this relationship is not necessarily linear (e.g., Harmon 1984, Jackson et al. 1990). In this study, we found that a linear model provided a best fit to our data. We used a regression model without constant because this model form was used in the FOFEM. It should be pointed out, however, that, by using this model form, the regression line was forced to pass the origin. Consequently, the reported $R^2$ was inflated. In fact, when a regression model with constant was used (Model [3]), the $R^2$ reduced from 0.965 to 0.407 leaving ~60% of the total variation in bark thickness unexplained by tree size. Therefore, future studies should explore the possibility of including additional variables in modeling bark thickness.

[3]     $BT = 0.435 + 0.031 * dbh$
         $P < 0.001, F_{1,179} = 123.978, R^2 = 0.407$

Compared to Model [3], which provided unbiased estimates across our data range (5 to 40 cm dbh), Model [2] tended to under-estimate bark thickness for smaller trees while over-estimated bark thickness for larger trees (Figure 1). Therefore, Model [3] was recommended for use in the modified FOFEM.

4.2. Tree Mortality Equations

We have developed a total of seven tree mortality models (Table 1). These models were grouped into four different model structures: recalibrated FOFEM model, modified FOFEM model, RH model, and complete model. Each model structure was fitted into the

data compiled in our study and used various combinations of variables. The recalibrated FOFEM model used the same two variables as in the current FOFEM (v5.2) software. The modified FOFEM model used the same two variables as well as their square transformations. The RH model used the bark thickness, relative humidity, and season of burn as predictors. The complete model used all possible variables. Except the recalibrated FOFEM, stepwise regression procedures were used in variable selection (see the attached manuscript #1 for details).
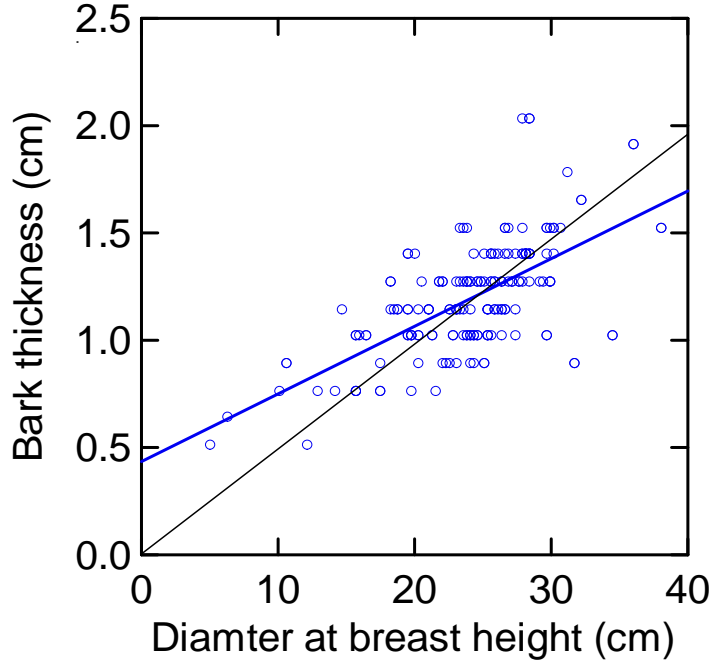


Figure 1. Scatterplot of bark thickness vs. diameter at breast height. The thick regression line is Model [3], and the thin regression line is Model [2].

The recalibrated FOFEM used the same two variables (bark thickness and proportion of crown scorch) as in the original tree mortality model within the FOFEM (v5.2) while the same variables plus their transformation were used in the modified FOFEM models. In addition, season of burn was also tested as an additional variable in modified FOFEM. In the end, we found the following predictive model was the best among all models tested within the two model structures:

[4] $\qquad p(mortality) = \dfrac{1}{1 + e^{-1.507 + 4.450\,SCH - 4.309\,SCH^2 + 12.788\,BT}}$

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Where SCH = Proportion of crown scorched (0-1); BT = Bark Thickness (cm). Cross-validation results indicated that Model [4] gave an overall corrected prediction of 87% and a corrected prediction of tree mortality event of 41%. When applying the model for prediction, we assumed that a probability of > 0.3 would result in mortality. This cutoff point, not the default 0.5, gave the model the best predictive power. This model represents a great improvement over the original tree mortality model in the FOFEM (v5.2) as well as the recalibrated FOFEM model of our study (Table 1).

**Table 1.** The final parameterized and calibrated models predicting the probability of longleaf mortality during a fire from all dataset and structure combinations. The general form for all models is:

$$P(Mortality) = \frac{1}{1+e^{\beta}}$$

| Model Structure | $\beta$ |
|---|---|
| Recalibrated FOFEM | $-0.220-1.916*BT+30.145*BT^2+1.442*SCH^2$ |
| Modified FOFEM | $0.128+1.457*SCH+27.276*BT^2-0.596*Summer-0.405*Winter$ |
| | $-0.521+1.512*SCH+26.791*BT^2$ |
| RH Model | $-1.496+6.258*RH^2+31.073*BT^2-0.659*Summer-0.407*Winter$ |
| | $-2.191+6.482*RH^2+30.076*BT^2$ |
| Complete Model | $-1.758+5.624*SCH-5.390*SCH^2+6.044*RH^2+32.456*BT^2-$ |
| | $0.494*Summer-0.551*Winter$ |
| | $-2.427+5.512*SCH-5.228*SCH^2+6.099*RH^2+31.805*BT^2$ |

*SCH = Proportion of crown scorched (0-1)*
*BT = Bark Thickness (cm)*
*RH = Relative Humidity (0-1)*
*Summer = 1 if burned during the summer, otherwise =0*
*Winter = 1 if burned during the winter, otherwise =0*

Although Model [4] use the same variables as the original FOFEM model, hence easier for implementation into the FOFEM software, its performance was much inferior compared to other models that included relative humidity as an additional variable (Table 1). Our best models developed in the study used a new variable, relative humidity, in addition to the two variables used in the original FOFEM (v5.2):

$$[5] \qquad p(mortality) = \frac{1}{1+e^{-2.191+6.482RH^2+30.076BT^2}}$$

$$[6] \qquad p(mortality) = \frac{1}{1+e^{-2.427+5.512SCH-5.228SCH^2+6.099RH^2+31.805BT^2}}$$

Where SCH = Proportion of crown scorched (0-1); BT = Bark Thickness (cm); RH = Relative Humidity (0-1). Cross-validation results indicated that these models gave an overall corrected prediction of 89.5% and 90% and a corrected prediction of tree mortality event of 62.2% and 64.5%, respectively, for Models [5] and [6]. When applying these models for prediction, we assumed that a probability of > 0.3 would result in mortality because this cutoff point gave the best predictive power. A graphical presentation of Model [4] is given in Figure 2, where probability of tree mortality increased with decreasing bark thickness and relative humidity.

As discussed in details in the attached manuscript #1, selecting the best model for predicting the mortality is a complex process. Based on biological and statistical considerations, we selected both Models [5] and [6] because these models would give the best predictions of longleaf pine tree mortality given the information available in our dataset and cross-validation tests.

Despite the proportion of crown scorch is not used, Model [5] had a very similar performance compared to Model [6]. This result indicated that proportion of crown scorch was not an important predictor of longleaf pine mortality. In fact, the recalibrated FOFEM model developed in our study indicated a negative relationship between tree mortality and the proportion of crown scorch. The modified FOFEM models and the complete models developed in our study displayed a bimodal "U" shape mortality response to crown scorch from 0 to 100%. These results support that % crown scorch is a poor indicator of tree mortality (Wade and Johansen 1986, Outcalt and Foltz 2004), and complete crown scorch may not result in tree mortality of longleaf pines especially when prescribed fires are conducted during the dormant season.

Because of the potential importance of fire season to longleaf pine mortality (Wade and Johasen 1986, Robbins and Myers 1990), we have also tested the usefulness of fire season as a predictor of tree mortality. The negative coefficients associated with summer and winter burn suggested that both summer and winter burn would reduce tree mortality when compared to spring burn. However, inclusion of fire season did not result in large improvement of overall mortality prediction. Although our data also included other variables described fire conditions, such as flame length, average rate of spread, and average wind speed, none of them was statistically significant to be included in tree mortality models.

Our mortality models were developed based on data collected from longleaf pine stands with a burn history (i.e., without pro-longed fire suppression), which, we believe, is typical to most prescribed fires currently conducted in longleaf pine forests. However, it has been observed that long-unburned longleaf pine forests may result in higher than expected mortality due to accumulation of duff. Mortality of large longleaf pine trees was observed due to damage to cambium and fine roots by smoldering duff fires without any crown scorch (Hiers et al. 2003). In this situation, duff consumption may be a useful predictor. For example, Varner et al. (2007) developed a simple equation specifically for this situation:

[7]     Log mortality (%) = -2.93 + 0.15 (% duff consumption)

Our study was performed using existing databases that were not collected specifically to answer the questions we have posed here.  Subsequently, there were certain inherent limitations in the data.  For example, our data are limited to relatively low intensity burns, as most were applied with the intention of minimizing mortality of canopy trees (longleaf pine) in order to sustain the site for long term research. It is true that most prescribed fires or natural fires in longleaf pine forest are inherently of low intensity, and would not cause a significant amount of tree mortality.  From a model fitting perspective, data collected over an entire range of fire intensity would be desirable. Furthermore, significant amount mortality may occur when reintroducing fire to long-unburned longleaf pine forests due to the increased fire severity resulted from smoldering of accumulated duff (Varner III et al., 2007). Therefore, our model may not be applicable to this situation.


**Figure 2.**  Response surface of Model [5] (RH model).  The model selected uses a cutoff value of 0.3, which means that any combination of relative humidity and bark thickness that results in a point on the surface where P(Mortality) > 0.3 results in mortality.
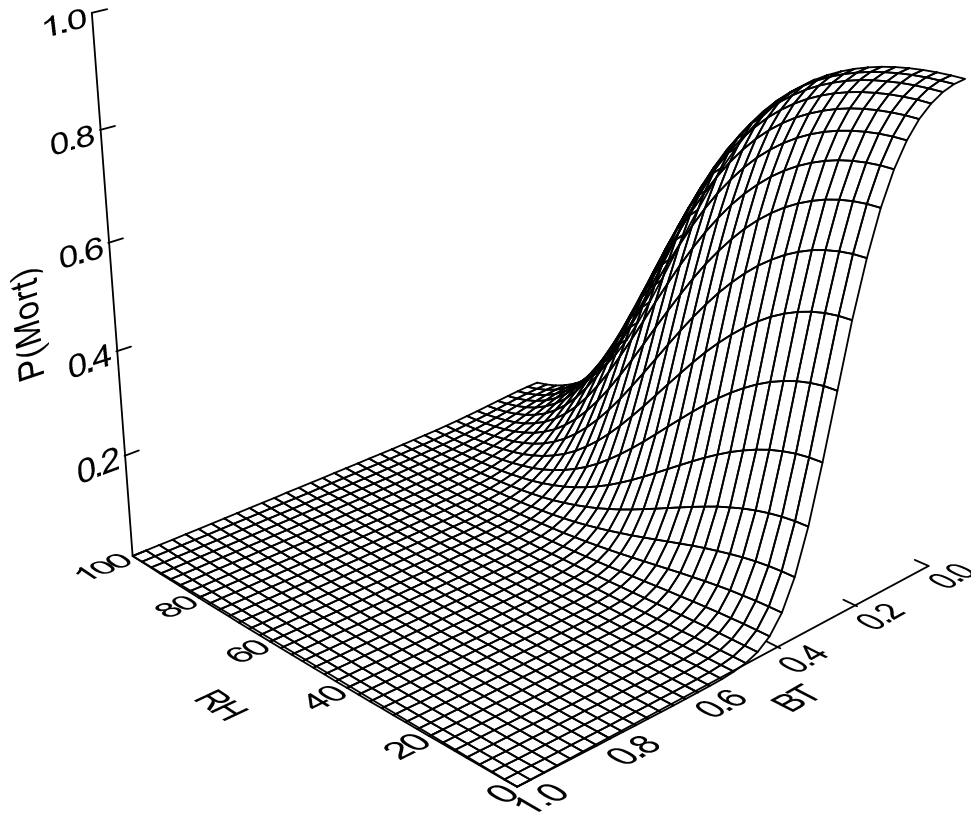
Fire behavior variables, such as flame length, residence time, or rate of spread, may be able to contribute some explanatory power to the model if it is observed at individual tree level. However, the data available to us reflected fire behavior at the site/stand level, which may be too course a resolution when investigating individual tree-level responses, especially given the heterogeneous behavior of forest fires. Conversely, a lack of scorch reflected in the crown does not indicate that there is no fire present at the base of the tree. For example, records from the Escambia burns indicate that burns routinely carried across the whole site even when no scorch was recorded on any of the trees. We suggest that further investigation of the relationship between fire damage and tree mortality proceed at an individual tree level, and pay specific attention to ambient conditions and the role that they play in fire effects.

4.3. Fuel Consumption Equations

FOFEM (v5.2) software used a mechanistic model to predict dead woody fuel consumption. Although we have tested FOFEM (v5.2) predictions on dead woody fuel consumption, we did not attempt to modify these mechanistic equations used in FOFEM (v5.2) software. We did, however, develop a few regression models for predicting fire effects on forest floor (litter and duff). These models were incorporated into the modified FOFEM.

Based on the pre- and post-fire destructive sampling of forest floor, we have developed the following model for predicting forest floor consumption:

$$Y = -3.893 + 0.944*X_1 - 0.078*X_2$$
$$R^2 = 0.897; n = 87; SEE = 4.07$$

Where $Y$ = forest floor consumption (Mg/ha), $X_1$ = forest floor amount before burn (Mg/ha), and $X_2$ = forest floor moisture content (% based on dry weight). We also tested moisture contents of other fuel components, but it was not significant.

Based on Brown's fuel transect measurements, we have also developed the following equation for predicting forest floor depth removal:

$$Y = -9.939 + 0.896*X - 29.582/X$$
$$R^2 = 0.892; n = 59; SEE = 2.99$$

Where $Y$ = forest floor depth removed (mm) and $X$ = forest floor depth before burn (mm). Forest floor moisture content was not significant, and therefore not included in the equation. Moisture contents of other fuel components were not significant either.

Based on duff-pin measurements ($n = 1607$), we also found about 5% complete forest floor removal (therefore, with mineral soil exposed), and about 6.8% zero forest removal.

4.4. Model Testing from Independent Data

Although models developed in our study fitted our data very well based on model statistics and cross-validation tests, the best way to validate these models and to evaluate their performance relative to those existing models used in FOFEM (v5.2) software is through independent testing. Collecting data for such independent testing, however, require time beyond the project period. Several federal agencies have already expressed strong interest in using models developed in the study. We plan to work closely with them on model applications and testing. Our federal collaborators are confident that they can incorporate model testing and validation into their ongoing and future research programs.

**5. Science Delivery and Application**

The status of each deliverables stated in the original proposal is given in Table 2.

The major deliverable of this project is a modified version of FOFEM used for longleaf pine and longleaf – slash pine cover types in the Southeastern US. Modifications to FOFEM software based on our study were made by the Rocky Mountain Research Station, and distributed through the fire.org webpage. Equations developed in the study have been implemented, and user documentation is being updated to explain the changes to the interface and some general comments. FOFEM is an approved Forest Service software product supported by a service level agreement between the Rocky Mountain Research Station and Forest Service Fire and Aviation. The WO Fire and Aviation Helpdesk provide first level support for customer needs.

As soon as the user documentation is updated, the modified FOFEM software will be made available to those agencies that have authority to conduct prescribed fires in the region. Several federal agencies, who have written support letters for the original proposal, have already expressed strong interest in using the modified FOFEM. We will be working closely with them on model applications. The modified FOFEM will also be used in the Fire Ecology course (FOR812) at Clemson University as a teaching tool for exploring first order fire effects.

**Table 2. Status of Proposed Deliverables**

| Deliverable | Description | Status |
|---|---|---|
| Web-publication | Project description | Delivered |
| Web-publication | Highlights of research progress and results | Delivered |
| Annual report to JFSP | Annual progress summary | Delivered |
| Conference presentation | Poster presentation at the Ecological Society of America The 91st Annual Meeting of Ecological Society of America. August 6-11, 2006. Memphis, TN. | Delivered |
| Conference presentation | Poster presentation at the Biennial Southern Silvicultural Research Conference | Not delivered* |
| **Conference presentation** | **Poster presentation at the 2nd Annual Fuels and Fire Behavior Conference. March 26-30, 2007. Destin, Florida.** | **Delivered (not in the original proposal)** |
| Annual report to JFSP | Annual progress summary | Delivered |
| Thesis | A M.S. thesis at Clemson University | Not delivered** |
| Technical paper | USDA Forest Service publication | In preparation; will be modified based on the final report. |
| Peer-reviewed publication | Publish research results on tree mortality and fuel consumption modeling (Target journal: *Forest Ecology and Management*) | Manuscript attached |
| **Peer-reviewed publication** | **Publish research results on The response of longleaf pine (*Pinus palustris*) bark thickness to variation in fire regime** (Target journal: *International Journal of Wildland Fire*) | **Manuscript attached (not in the original proposal)** |
| Software | A modified version of FOFEM | Delivered |
| Final report to JFSP | Include a statement of how the deliverables listed in the proposal match what has actually been produced, paper and electronic copies of all completed deliverables, and a brief summary of what was learned from the investigation. | Delivered |

*We presented our results in another conference. **We hired a research assistant with MS degree (Steve Wangen) working on the project. Therefore, no MS thesis was produced.

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**Manuscript #1: Evaluation of longleaf pine (*Pinus palustris*) fire mortality models for incorporation into the FOFEM software**

**ABSTRACT**

Millions of acres of pine dominated forests are burned each year in the Coastal Plain region of the Southeastern US. Many prescribed fires in the southeast are conducted to restore or maintain longleaf pine forests, once a dominant feature in the Southeast but now only occupying less than 5% of their pre-settlement extent. To better plan for fire effects, predictive models such as FOFEM (First Order Fire Effects Model) are needed. Currently, FOFEM has been used by thousands of fire and land managers across the United States. Based on data compiled from published and unpublished prescribed fire studies, we evaluated the existent longleaf pine tree mortality model in FOFEM, and developed new models for predicting fire-induced tree mortality in longleaf pine forests. We developed a total of 14 logistic tree mortality models, and selected two models for applications based on a suite of techniques that evaluate model behavior and model discrimination capacity. The first selected model used relative humidity squared and bark thickness squared as predictors while the second selected model used proportion of scorch, proportion of scorch squared, relative humidity squared, and bark thickness squared as predictors. Incorporating these models into FOFEM should greatly improve longleaf pine mortality prediction.

## 1. INTRODUCTION

Longleaf pine (*Pinus palustris* Mill.) was once the dominant overstory tree in the upland communities of the southeastern United States (Noss et al. 1995). The species inhabits a range of sites from wet, poorly drained flatwoods to rocky outcrops, but is predominately found in sandy well drained areas. Longleaf pine is postulated to have covered as much as 92 million acres when the first European settlers arrived on the coastal plain of the Carolinas and Georgia (Landers et al. 1995, Boyer 1990). Due in part to a combination of resource extraction, intentional species conversion, fire exclusion, and land use changes (i.e., conversion to agriculture), the current extent of longleaf pine dominated stands is estimated at around 10% or less of the pre- European settlement coverage (Frost 1993, Kelley and Bechtold 1990), while remaining old-growth stands are projected to be even more rare (Varner and Kush 2004). The current distribution of longleaf pine has prompted the classification of the species as 'vulnerable' by the World Conservation Union, which means its current status is defined as facing a high risk of extinction (IUCN 2006). However, a recent increase in interest as both an economic and ecological resource has fueled newfound interest in the management and restoration of longleaf pine, and may serve to move the species away from the threat of extinction.

The historical importance of fire in maintaining the longleaf pine ecosystem has been well documented (Heyward 1939, Barnett 1999, Komarek 1974, Hudson 1982, Stanturf et al. 2002). Today fire is being introduced in a purposeful and controlled manner to these stands through the use of prescribed burns in order to recreate the pre-settlement conditions in which longleaf flourished. However, the use of fire as a management tool creates the risk of losing trees to fire-induced mortality. This tradeoff

becomes unavoidable when management goals include restoration of longleaf stands to presettlement conditions. Therefore, a balance must be sought between keeping fire at adequate levels at which restoration goals can be achieved while the mortality of longleaf pine trees is minimized. As a means to strike this balance, a straightforward and easily applied model that provides accurate predictions of mortality based on easily measurable inputs becomes necessary.

The ability to predict which trees in a stand would succumb to fire damage, when prescribed fires are conducted, can help improve both the ecological and economic efficiency of stand management. Such predictions can assist land managers in planning prescribed burns to minimize loss while meeting other management priorities, such as control of competition or seedbed preparation. When necessary, these predictions can also be used to plan and implement removal strategies when fire intensities are prescribed high enough to result in partial mortality of some trees in the stand. Salvage operations could be targeted to preemptively remove trees that will eventually die from fire damage before the economic value is degraded by insects or pathogens which can also threaten the health of the rest of the stand once established.

Previously, the Joint Fires Science Program (JFSP) has supported the development of the First Order Fire Effects Model (FOFEM) at the USDA Forest Service Fire Science Laboratory in Missoula, Montana. FOFEM is a computer program that was designed to meet the needs of resource managers, planners, and analysts in predicting and planning for fire effects, including tree mortality. The mortality models used in FOFEM are based on empirical relationships, predicting probability of death based on bark thickness and % crown scorch. Despite its intended national scope, user feedbacks

indicate that FOFEM significantly over predicted tree mortality when applied to longleaf stands in the southeastern US. In order to correct the over-prediction of tree mortality by the current version of FOFEM, we performed an extensive search to locate existing data that contains information regarding fire behavior and tree mortality in longleaf pine - stands. These data were used to recalibrate the existing FOFEM model while at the same time formulate a number of new models to examine the interplay of fire damage and longleaf mortality. We then employed a number of techniques to examine the discrimination capacity of each of the developed models in order to determine which best predicted tree mortality.

## 2. METHODS

### 2.1. Data Sources

Data for the development of the tree mortality model was assembled from three different locations: the Solon Dixon Forestry and Education center near Andalusia, Alabama, the Myakka River State Park near the gulf coast in middle peninsular Florida, and the Escambia Experimental Forest located just outside of Brewton, Alabama. These locations were chosen from an extensive search for datasets that contained enough information to examine the relationship between scorch severity and mortality of longleaf pines at the widest geographical scale possible. We located these datasets through a combination of extensive literature search and personal communications with experts in this field, including our project cooperators.

The data from the Solon Dixon and Myakka sites are for individual fire events: a prescribed fire at Solon Dixon and an accidental fire at Myakka State Park. The data

from the Escambia Experimental forest are from an ongoing prescribed fire study, and data have been collected since the study's inception in 1973. This study consisted of biennial burns conducted at different seasons, and Boyer (1983) provides a detailed description of the site and treatments for the study.

Data from all sites were reduced to the maximum number of explanatory variables that were common to all sites. Individual tree data from all sites included stem diameter measured at breast height (dbh, 1.4m), severity of crown scorch (% of live crown scorched), and tree status (live or dead) both before and at least one year after the sites had been burned. In total there were 4968 individual observations recorded: 151 from the Myakka state park, 516 from Solon Dixon, and 4301 from Escambia. Data collected for fire conditions included flame length, average rate of spread, average wind speed, the season of the burn (spring, summer, or winter), and average relative humidity (%) during the burn.

*2.2. Model Development*

*2.2.1. Bark Thickness*

In order to make the data directly compatible with the mortality model used in the FOFEM software, we needed to convert stem diameter to an estimate of bark thickness. The FOFEM software contains a linear regression that relates longleaf pine stem diameter to bark thickness. In order to eliminate this conversion as a potential source of error or bias and to insure that the model currently used in the FOFEM software was applicable to the trees in our datasets, we collected bark thickness measurements from 180 longleaf pine trees from the Escambia Experimental Forest. These data were used to develop an

independent predictive equation.  Measurements of bark thickness were taken from a random subset of trees in each treatment replication found on the experimental forest. Bark thickness measurements were obtained using a Haglof Barktax bark thickness gauge.  Four thickness measurements were taken from each tree in each cardinal direction and then averaged to obtain the estimate of bark thickness.  A model was then fit using linear regression techniques (Neter et al. 1996) performed in SYSTAT (v.11, SSI Richmond, Ca) to relate bark thickness to dbh.

*2.2.2. Mortality Function*

*2.2.2.1. Model Structure*

A logistic function was chosen to model tree mortality for three reasons: 1) it is the expression used in the FOFEM software, 2) it has proven very effective when applied to binary processes such as tree mortality (Monserud 1976, Reinhardt and Ryan 1988, Ryan and Reinhardt 1988, Hosmer and Lemeshow 1989, Dobbertin and Brang 2001, Hely et al. 2003, McHugh and Kolb 2003, Regelbrugge and Conard 1993, Rigolot 2004), and 3) the relaxed assumptions on the data distribution proved much more appropriate for our datasets than those required for performing a discriminant analysis (Press and Wilson 1978).

Four basic model structures were utilized to develop the new models of tree mortality based on our data, with the goal of selecting the best model based on a combination of model fit and model simplicity.  These four model structures are 1) a recalibrated FOFEM model, 2) a modified FOFEM model, 3) an RH model, and 4) a complete model.  The first two structures (the recalibrated and modified FOFEM models)

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were based on the existing model structure currently used in the FOFEM software. The last two model structures were allowed to deviate from the existent model structure used in the FOFEM software, and were developed dynamically with an emphasis on achieving the best model fit with the available data through the use of a stepwise procedure.

The recalibrated FOFEM model consisted of re-calibrating the coefficients of the tree mortality model currently used in the FOFEM software based on our datasets. This model structure would be the easiest to re-incorporate back into the FOFEM software as the only change would be to adjust the coefficients specific to longleaf pine.

In the modified FOFEM model, we used the same basic variables (% scorch and bark thickness) as in the original FOFEM model, but square root and squared transformations were performed on these independent variables in an attempt to improve model fit. A manual stepwise procedure was used to select appropriate variable combinations based on the predicted chi-squared significance level in SYSTAT (SSI, Richmond, Ca). Inclusion of a variable into the model, during the stepwise procedure, was based on the predicted chi-squared significance level of the variable not exceeding an alpha level of 0.15, while removal of a variable once in the model was dictated at $\alpha <$ 0.10. Implementing the modified FOFEM model into the FOFEM software should also be relatively easy because no additional new variables need to be added and defined in the software.

The other two models deviate from the model structure used in the FOFEM program in order to investigate if a better prediction of tree mortality could be obtained by exploring the influence of other possible mechanisms on tree mortality. First, we assessed the potential of the other variables (flame length, rate of spread, wind speed,

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season of burn, and relative humidity) by assembling a variety of models using a holdout cross-validation technique. Data were randomly splitted into two groups: the training set and the validation set. The training set (80% of the observations) was used to parameterize the model while the validation set (20%) was retained to assess the fit of different models. Variables to be included in different model structures were selected using the stepwise procedure described above. Exhaustive testing using this technique led us to conclude that the best improvement in explanatory value could be achieved by including variables representing a measure of relative humidity at the time of the burn and the season during which the burn was conducted.

Inclusion of the relative humidity variable in the model development through stepwise regression procedure allowed us to derive two additional model configurations: a combination of relative humidity and bark thickness (the RH model) and a combination of bark thickness, relative humidity, and scorch levels (the complete model). Due to the uncertainty on the effects of season of burn on tree mortality, we tested each model structure in two forms: with and without season of burn included as an additional variable. While the cross-validation technique allowed us to assess the fit of the model using an independent dataset, it has been suggested that the entire dataset be utilized for calibrating the final classification rule (Rencher 1995). For this reason the resultant models from the cross validation were re-calibrated using the entire dataset, and only these versions are considered for actual application.

*2.2.2.2. Calibration Datasets*

The complete dataset was heavily biased towards scorch values of zero, as the majority of trees in the study did not reflect any scorch during the fires (3597 of 4968 observations reported values of 0% crown scorched) and mortality events displayed on average less scorch damage than the individuals that survived (t-test; $P = 0.003$). We attempted to overcome this inherent problem by forming different subsets of the data for model calibration. Specifically, we formed subsets of data that allowed us to mitigate the influence of the unexpectedly high number of observations with no recorded scorch damage while maintaining the integrity of the statistical analyses. As a result, we used three different datasets to parameterize each of the four model structures: 1) the complete dataset, 2) the SCH > 0 subset, and 3) a stratified random subset. The complete dataset consisted simply of the complete set of observations. By removing any observations where the level of crown scorch was equal to zero, the SCH > 0 subset effectively confining the dataset to trees that had discernibly been influenced by the fires. The stratified random subset consisted of a random sample of observations stratified by severity of crown scorch into one of eleven groups: 0%, 0<x<10, 10≤x<20, 20≤x<30, 30≤x<40, 40≤x<50, 50≤x<60, 60≤x<70, 70≤x<80, 80≤x<90, x≥90. The size of each group was then reduced to 83 observations (the number of observations in the smallest group) by randomly selecting individuals from the group for removal. By doing so, we have achieved equal representation of trees with different degrees of scorch by fire.

*2.2.3. Model Selection*

*2.2.3.1. Examination of Model Behavior*

After calibrating the models, we examined the relationships between the different variables in each model to see if they behaved as expected.  We examined the relationships by plotting model output (i.e., the probability of mortality) against the entire range of a single independent variable while holding all other independent variables constant.  We expected that scorch would be positively correlated with the probability of mortality and bark thickness would be negatively correlated with the probability of mortality, based on findings during the original FOFEM model development (Ryan and Reinhardt 1988).  We also expected that relative humidity would be negatively correlated with the probability of mortality, reflecting how relative humidity levels in the atmosphere affect the moisture content of the fine fuels that typically serve as the primary fuel source in longleaf stands subject to periodic fires.

*2.2.3.2. Model Discrimination Capacity*

Each of the possible model/dataset combinations were tested against the entire dataset of observations.  The predicted response was then classified according to its concordance with the observed response as a true positive (TP), a false positive (FP), a true negative (TN), or a false negative (FN).  This results in a 2x2 confusion matrix for each developed model (Table 1).  Since the accuracy of the response from binary models can be very sensitive to the probability threshold at which the model response changes (Bradley 1996, Fielding and Bell 1997, Manel et al. 2001), we calculated the confusion matrix for each model/dataset combination with nine different threshold values (the value which, when exceeded, results in the model returning a positive response).  The traditional practice assumes that the best classification rule has a threshold value set at

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0.5.  Testing different threshold values allowed us to examine the models' responses in two additional ways: by examining the Receiver Operating Characteristic (ROC) curve produced by each model and by evaluating each model/threshold combination independently of the same model with the other threshold values.

ROC curves were used to summarize the range of responses contained in the confusion matrix across the range of the threshold values.  ROC curves are constructed by plotting the probability of a true positive [calculated as $TP/(TP+FN)$] against the probability of a false positive [$FP/(FP+TN)$] across the range of possible threshold values.  The point (0, 1) represents a perfect condition where the probability of a false negative is minimized and the probability of a true positive is maximized.  Typically, the closer a ROC curve approaches this point, the better its performance (Manel et al. 2001, Saveland and Neuenschwander 1990).  We developed an ROC curve for each of the models and overlaid them to examine if any of the models displayed what appeared to be substantially different performances than the others.

The confusion matrices for each of the model/threshold combinations were then used to calculate a suite of indices that can be used to gauge how well the model predictions are able to match the actual observed outcomes.  The indices calculated (Table 2) include: overall classification rate (the proportion of observations correctly classified), positive predictive power (the proportion of predicted positives that are actually positive), sensitivity (the proportion of actual positives correctly classified), specificity (the proportion of actual negatives correctly classified), and the odds ratio (the ratio of correctly assigned outcomes to incorrect outcomes; Manel et al 2001).  We also calculated a Kappa statistic (proportion of specific agreement; Fielding and Bell 1997),

and a normalized mutual information statistic; both of these produce values between 0 and 1, with higher numbers indicating a better model fit (Manel et al 2001). Careful interpretation of these scores is critical, as unequal group sizes (as between the live and fire-killed groups in our dataset) can have a strong influence on the indices (Fielding and Bell 1997, Hosmer and Lemeshow 1989), although the Kappa statistic is designed to account for such situations (McGinn et al. 2004).

Using these indices, we reduced the number of models developed in the study to only four models for final consideration. To do so, we first selected the model that produced the best overall classification rate, a criterion that is often used for choosing the best fitting model in ecological applications (Fielding and Bell 1997, Manel et al 2001). For the other three, we simply selected the models that predicted over 50% of the mortality events correctly (TP > 292). Our selection of a final model was based on indices that best reflected the model's ability to correctly classify the mortality events (specifically a high number of true positives and a high sensitivity score) by maximizing the probability of producing a true positive response. Our selection criteria effectively optimize the response bias in a conservative manner, which is more fitting to the low probability of mortality occurrence in our dataset (Swets and Pickett 1982).

## 3. RESULTS

### 3.1. Bark Thickness

Based on our data, the following regression equation was developed to predict bark thickness at breast height (*BT*) from dbh:

$$BT = 0.048 * dbh$$

$$P < 0.001, F_{1,179} = 934.949, R^2 = 0.965$$

Not that we did not include a constant in the equation in order to make it comparable with

the bark thickness prediction equation used in the FOFEM software. Our model was

nearly identical to the equation currently used to predict longleaf pine bark thickness in

the FOFEM software (*BT = 0.049* * DBH, Duncan Lutes, pers. comm.). It should be

pointed out, however, that, by using this model form, the regression line was forced to

pass the origin. Consequently, the reported $R^2$ was inflated. In fact, when a regression

model with constant was used, the $R^2$ reduced from 0.965 to 0.407 leaving ~60% of the

total variation in bark thickness unexplained by tree size:

$$BT = 0.435 + 0.031 * dbh$$

$$P < 0.001, F_{1,179} = 123.978, R^2 = 0.407$$

When these two models were compared, we found regression with the constant

produced unbiased estimates across our data range (5 to 40 cm dbh) while regression

without constant under-estimated bark thickness for smaller trees and over-estimated bark

thickness for larger trees (Figure 1). Therefore, regression with constant was

recommended for use in the FOFEM software.


*3.2. Development of Potential Mortality Functions*

Using the stepwise logistic regression procedure, we constructed a total of 14

model variations for predicting the death of longleaf pine trees using a combination of

different variables (Table 3). Each individual model in Table 3 is identified by a

combination of the basic model structure and which dataset was used for the calibration

of the model.  The use of $\alpha < 0.10$ cutoff for the inclusion of a variable into the model

was somewhat arbitrary, but none of the variables included (other than those forced to

recreate the FOFEM model structure) produced a significance value greater than $P =$

0.04.

The re-calibration of the original FOFEM model (which, by definition, includes

the terms bark thickness, bark thickness squared, and scorch height) did not perform as

well as hoped. When the complete dataset was used for the recalibration, the chi-squared

p-value of both the intercept ($P = 0.574$) and the bark thickness ($P = 0.553$) terms were

insignificant in the model (Table 3; Model [3]).  When we recalibrated the original

FOFEM model with the other two datasets, we found that none of the independent

variables used in that model were significant (Table 3; Models [1] and [2]).

Because of its poor performance, the original FOFEM model was modified by

maintaining the same suite of potential variables (bark thickness and proportion of crown

scorch, as well as their squared transformations), but the final decision on the inclusion of

any variable into the model was determined by the p-values obtained from the stepwise

procedure.  This process resulted in the development of three additional models.  The first

model, calibrated using the stratified random subset of our data, included the proportion

of crown scorched, the proportion of crown scorched squared, and the bark thickness as

predictors (Table 3; Model [4]).  The second, parameterized using the complete dataset,

included the proportion of crown scorch, bark thickness squared, and dummy variables

representing the season of the burn as predictors (Table 3; Model [5]). The third, also

parameterized using the complete dataset, included the proportion of crown scorched and

bark thickness squared as predictors (Table 3; Model [6]). Using the SCH > 0 subset of our data for calibration did not produce a significant model.

By using a combination of relative humidity and bark thickness (the RH model) we were able to develop three additional models for predicting tree mortality. The first version of the RH model was developed using the stratified random subset of our data, and included relative humidity squared and bark thickness as predictors (Table 3; Model [7]). The second and third versions of the RH model were both developed using the complete dataset, and included relative humidity squared, bark thickness squared, and with (Table 3; Model [8]) or without (Table 3; Model [9]) the season of burn as predictors. No combination of bark thickness and relative humidity variables were significant when parameterized using the SCH > 0 subset of our data.

The complete model form (i.e., predictors were selected from the pool of all available variables using a stepwise technique) produced five versions of tree mortality model depending on the dataset used for model fitting. The complete dataset produced two models that utilized a combination of proportion of crown scorched, relative humidity, bark thickness, and with (Table 3; Model [13]) or without (Table 3; Model [14]) the season of burn as predictors. The stratified random subset resulted in a model that contained the proportion of crown scorched, bark thickness, and relative humidity as predictors (Table 3; Model [10]). Based on the SCH > 0 subset of our data, two models were developed: one used bark thickness squared as sole predictor (Table 3; Model [12] and another used bark thickness squared plus the season of burn as predictors (Table 3; Model [11]) .

*3.3. Model Selection*

*3.3.1. Model Behavior*

Out of the 14 model variations that were developed, only six of them display the expected correlation between crown scorch severity and mortality: the RH models calibrated using either the complete data or the stratified random subset of our data (Models [7-9], in Table 3), and the recalibrated FOFEM (Model [2] in Table 3) and complete models calibrated using the SCH>0 subset of our data (Models [11-12] in Table 3). Of the others, two of the recalibrated FOFEM models, which used the stratified random subset and the complete dataset, showed a negative correlation between crown scorch severity and the probability of mortality. The other six models exhibit a bimodal 'U' shaped response with regard to probability of mortality as crown scorch ranges from zero to 100% (Figure 2). This was not entirely unexpected as our dataset is essentially bimodal, with a high number of mortality observations occurring with no reported crown scorch, complemented by another peak in mortality at 100% crown scorch.

*3.3.2. Model Discrimination Capacity*

The fourteen model variations were tested at each of the nine different threshold levels ranging from 0.1 to 0.9 in 0.1 increments (for a total of 126 model x threshold combinations). This was done by comparing their output to the observed conditions using the complete dataset. The overall classification rate was good for all models, ranging from a low of 70.9% of observations correctly classified up to 91.1%.

Based on the confusion matrices of the 126 model x threshold combinations, we eliminated all model x threshold combinations that have sensitivity < 0.5, positive

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predictive power < 0.5, and/or the overall correct classification rate < 0.5. After removing those models, only four model x threshold combination remained for consideration (Table 4). These four models were all parameterized using the complete dataset. Two were parameterized using the complete model form (derived from an unrestricted stepwise selection procedure on all the available variables except for the season of burn), with cutoff points of 0.4 and 0.3 (hereafter referred to as Models [15] and [16]). The third was also parameterized using the complete model form, but included the season of burn variable as a predictor, with a cutoff point of 0.3 (Model [17]). The fourth was from the RH model structure, with 0.3 as the cutoff value (Model [18]). The highest overall classification rate (0.9124) and positive predictive power (0.6630) was achieves by the complete model (without the season of burn variable) when calibrated using the complete dataset with a threshold value of 0.4 (Table 4; Model [15]).

The ROC curves of the final three model forms (complete models without the season of burn as a predictor, complete model with the season of burn as a predictor, and RH model without the season of burn as a predictor) displayed very similar behavior (Figure 3), and did not contribute much to determining which model provided the best fit. It did, however, reveal that all of them showed significant improvement over the original FOFEM model (Figure 3). The position of the specific cutoff levels for each model is also displayed on the graph (Figure 3). Given their relatively low position on the x-axis, it becomes obvious that the criteria utilized in selecting these models is not directly compatible with traditional ROC curve analysis, in which the responses closest to the point (0,1) are considered to be most desirable (Robertson et al. 1983, Manel et al. 2001).

Models [15] and [17] correctly predicted just over half (51.9% and 50.9%, respectively) of the actual mortality events, compared to Models [16] and [18] that predicted 64.6% and 62.2% of the mortality events. Since the emphasis is on the correct prediction of these relatively rare events, Models [15] and [17] were dropped from consideration. Models [16] and [18] were nearly identical in all of the comparisons made from their respective confusion matrices. As these matrices could not provide a definitive answer to which provided better estimations, Model [18] was selected for application, as it is a simpler model with fewer parameters. However, when the proportion of crown scorch is measured, Model [16] could be used as well, without any immediately perceptible drawbacks in predictive power. The graphical form of Model [18], which shows the change of the probability of mortality in relation to bark thickness and relative humidity, is given in Figure 4. A combination of thin bark (< 0.5 cm) and low relative humidity would likely result in high tree mortality.

The tree mortality model currently used in the FOFEM (v5.2) software significantly over-predicted the occurrence of mortality in our dataset, projecting 99.6% mortality of the 4968 observations (using a cutoff value of 0.5; Table 5) compared to the 11.8% that actually died. The overall classification rate for the original FOFEM model was just below 13%. The best modified FOFEM model, although much improved over the original FOFEM model, did not perform well when compared to the models selected in Table 4. The positive predictive power, when using a cutoff value of 0.2, was only about 41% (Table 5).

## 4. DISCUSSION

### 4.1. Model Selection

Our initial goal for this project was to develop a working model that could accurately predict the mortality of longleaf pine trees after fire. To facilitate the model implementation into the FOFEM software, it is desirable that our newly developed models should work within the confines of the FOFEM model structure by using bark thickness and crown scorch as the predictive variables. All of the models tested in our study represent a substantial improvement over the original FOFEM model that is currently used to predict the mortality of longleaf pine after fire. The best predictions were produced by using a model that combined relative humidity and bark thickness. Unfortunately neither this model nor any of the other better fitting models can be re-incorporated into the FOFEM program without substantial modification of the software, as they all require inclusion of additional variables outside of what FOFEM already requires. The models that could be easily reincorporated (those that limited the variables to a combination of bark thickness and crown scorch severity) proved relatively unreliable in predicting longleaf pine mortality after fire. Even the best of these models, the modified FOFEM model parameterized using the stratified random subset and a cutoff value of 0.2, still showed a poor predictive power when compared to the other models selected for the application.

Modeling post-fire tree mortality using crown scorch and bark thickness has proven successful in a wide range of species (Borchert and Schreiner 2002, Fowler and Sieg 2004, Rigolot 2004, Ryan and Reinhardt 1988). As a result, FOFEM has adopted a model structure using crown scorch and bark thickness as predictors. However, when

applied to predicting longleaf pine mortality, this model structure performed rather poorly, which was unexpected. While some of the better fitting models developed in our study utilized only relative humidity and bark thickness, most models combined these two variables with a measure of crown scorch and (occasionally) and the season of burn. Clearly, including variables that affect fire behavior (i.e., relative humidity and the season of burn) and tree physiology (the season of burn) have improved model performance. These variables are easily measured, and should become a part of standard documentation of each prescribed fire.

Our model results suggest that the mechanisms of fire-induced tree mortality in longleaf pine may differ from most other conifer species. The fire regime in longleaf pine forests is characterized as frequent surface fire with relatively low intensity. Our data indicated that majority (~72%) of trees did not record any crown scorch during prescribed fire, likely due to low fire intensity. Longleaf pine has well developed fire protection traits (e.g., thick bark, excellent self-pruning, meristem protection) and tree mortality due to fire are typically low (less than 10%). Our data indicated that mortality events display on average less scorch damage than the individuals that survive, indicating that crown scorch is neither the major cause nor a good indicator of fire damage to longleaf pine trees. The high tolerance of longleaf pine to crown scorch is well documented (Wade and Johasen 1986, Outcalt and Foltz 2004). Mortality in longleaf pine may, for example, be more closely tied to environmental conditions. The inclusion of relative humidity in our models may serve as a measure of fuel status available in our dataset. Fuels in longleaf stands are typically smaller fine fuels, which react quickly to ambient conditions. Both the moisture content and the duration of fuel buildup can have

a large effect on the amount of damage conveyed to existing trees, both above and below ground.

*4.2. Model Diagnostics*

The techniques used in the evaluation of model performance are an important consideration when choosing between multiple models. Overall accuracy assessments are not always the best guide, and model usefulness and appropriateness must be taken into consideration. In our study, the model with the highest accuracy was the one with the highest overall classification rate. The use of this measure for model selection assumes that there is an equal tradeoff between correctly classifying a positive response (sensitivity) and a negative response (specificity). Standard ROC analyses (such as visual inspection or area under curve (AUC) calculations) also place equal importance on sensitivity and specificity (and subsequently on type I and type II errors), but can be modified with a weighting scheme if the relative importance of the two is known (see Manel et al. 2001, Zweig and Campbell 1993). In some cases the assumption of equal importance between sensitivity and specificity may be appropriate, but in other situations it may be important to consider the tradeoffs between the two, especially in datasets with relatively low prevalence of events (i.e., mortality in our case) actually occurring (Fielding and Bell 1997, Manel et al. 1999). For example, in a dataset where prevalence = 0.10 (10% of the observations are a positive event, in our case, tree dies due to fire), the entire dataset could be classified as producing a negative result without registering a single positive event, and the overall accuracy rate would still be 90%. For this reason, development of any model should at least take into account the level of prevalence of an event in the dataset. If data are heavily biased in one direction or another, further

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evaluation of the model fit using the suite of indices available via the confusion matrix should be used. Therefore, it was not surprised that our model with the highest overall classification accuracy did not correctly predict mortality events as accurately as the models selected based on their sensitivity scores.

Reliance on the indices derived from the confusion matrix also allowed us to examine each model/threshold combination independently. Since our classification rule is most likely to be somewhat inflexible if it were to be implemented into a software program, it is important that we designate the appropriate threshold between a positive and negative response. In similar situations, where the threshold value is not likely to be adjusted by an end user, we suggest that models be chosen based on their performance at a specific threshold, as opposed to examining the performance of the model across all threshold values.

*4.3. Further Research*

Our study was performed using existing databases that were not collected specifically to answer the questions we have posed here. Subsequently, there were certain inherent limitations in the data. For example, our data are limited to relatively low intensity burns, as most were applied with the intention of minimizing mortality of canopy trees (longleaf pine) in order to sustain the site for long term research. It is true that most prescribed fires or natural fires in longleaf pine forest are inherently of low intensity, and would not cause a significant amount of tree mortality. From a model fitting perspective, however, data collected over an entire range of fire intensity would be desirable. Furthermore, significant amount mortality may occur when reintroducing fire

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to long-unburned longleaf pine forests (Varner III, 2007). This elevated tree mortality is actually caused by the increased fire severity due to smoldering of accumulated duff. The degree of duff consumption has been found to be a good predictor of longleaf pine tree mortality (Varner III, 2007).

Fire behavior variables, such as flame length, residence time, or rate of spread, may be able to contribute some explanatory power to the mortality model if it is observed at individual tree level. However, the data available to us reflected fire behavior at the site/stand level, which may be too course a resolution when investigating individual tree-level responses, especially given the heterogeneous behavior of forest fires. Conversely, a lack of scorch reflected in the crown does not indicate that there was no fire present at the base of the tree. In fact, our data from the Escambia burns indicated that fires routinely carried across the whole site even though no scorch was recorded on any of the trees. We suggest that further investigation of the relationship between fire damage and tree mortality proceed at an individual tree level, and pay specific attention to ambient conditions and the role that they play in fire effects.

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Figure 1. Scatterplot of bark thickness vs. diameter at breast height. The thick line represents the regression equation with constant while the thin line represents the regression equation without constant.
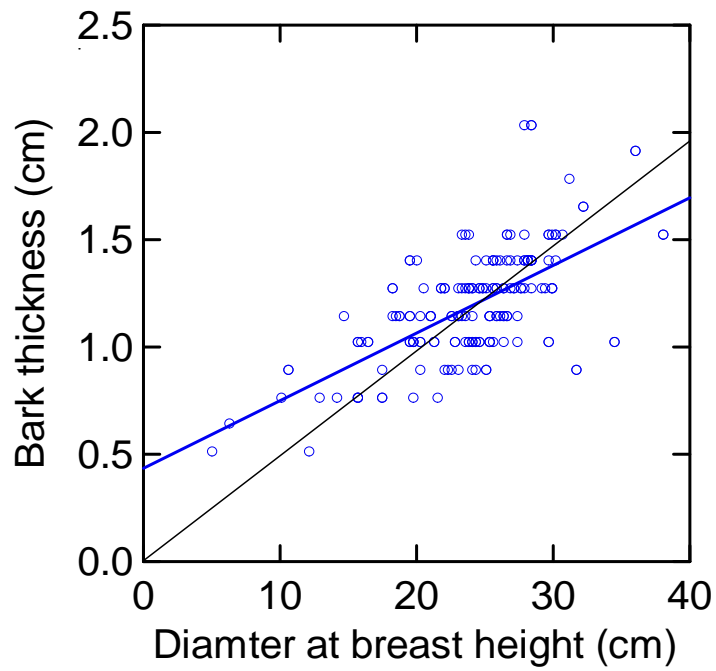
**Figure 2.** The U-shaped response of the probability of mortality vs. crown scorch for four of the model configurations. The expected response would be a positive correlation between the two axes. The four curves are Models [4], [13], [5], and [10], respectively, from left to right. Each model is given in Table 3.
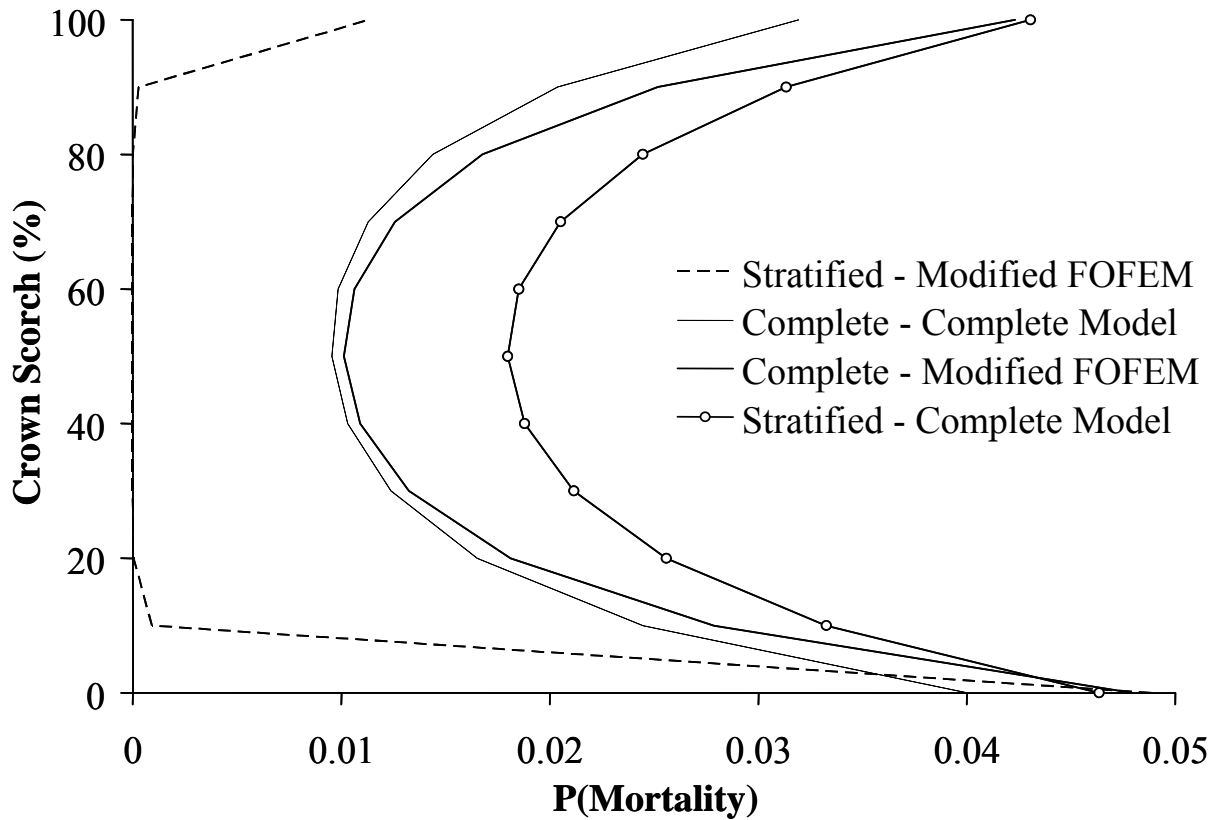
**Figure 3.**  Receiver Operating Characteristic (ROC) curves of the final four model configurations along with the original FOFEM

model for comparison.  The model cutoff points that were utilized in the final consideration are also shown.
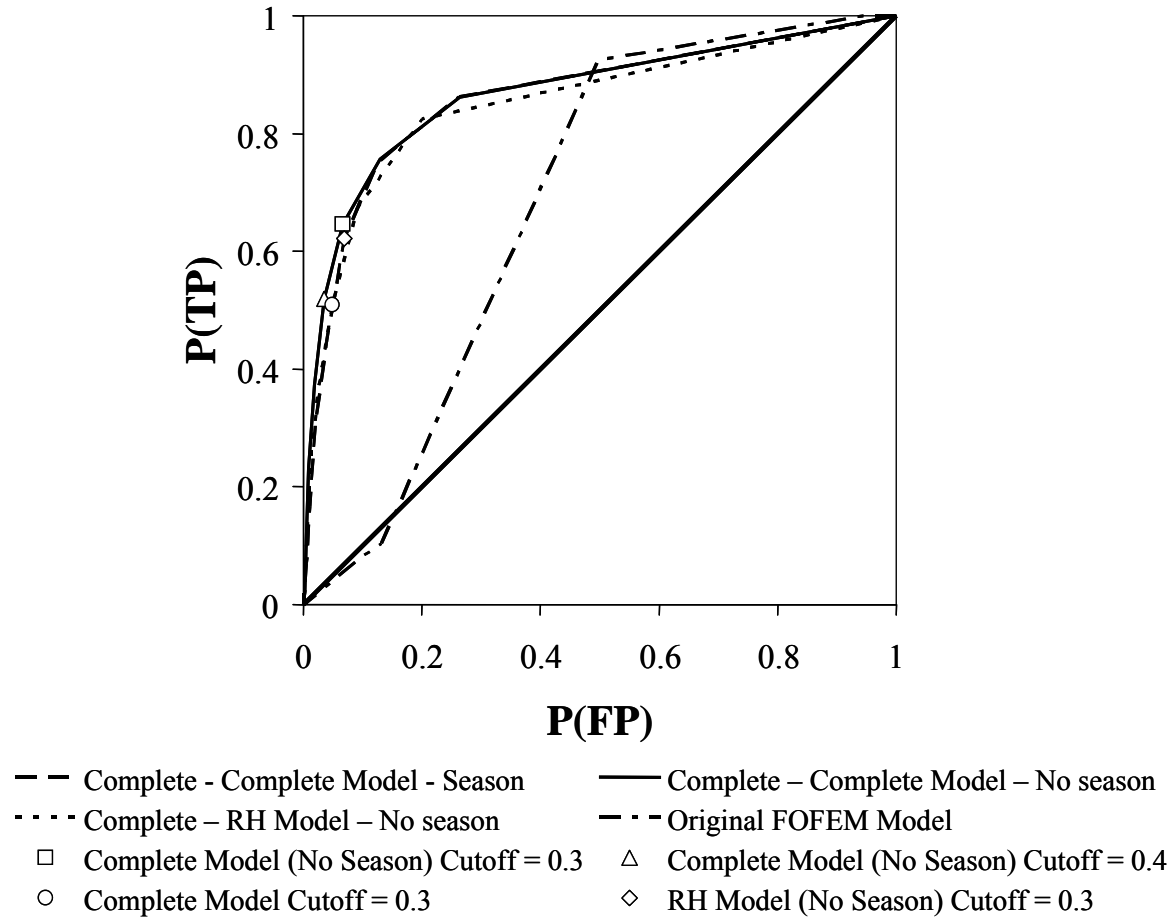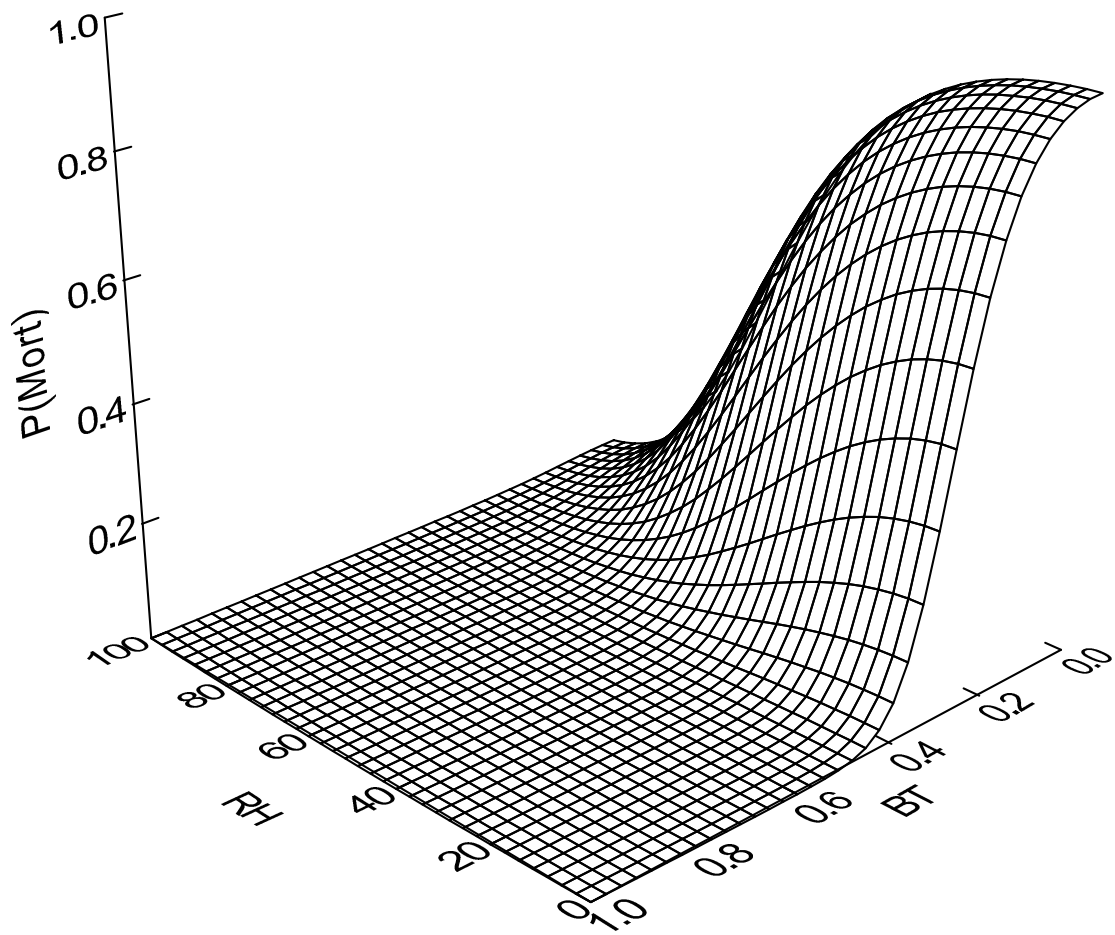
**Figure 4.** Response surface of the selected RH model (Model [9]; Table 3). The model selected uses a cutoff value of 0.3, which means that any combination of relative humidity and bark thickness that results in a point on the surface where P(Mortality) > 0.3 results in

**Table 1.** Theoretical confusion matrix setup used to determine model discrimination ability.

|  |  | ACTUAL OUTCOME | |
|---|---|---|---|
|  |  | **Dead** | **Alive** |
| **MODEL PREDICTION** | **Dead** | True Positive (TP) | False Positive (FP) |
|  | **Alive** | False Negative (FN) | True Negative (TN) |

**Table 2.** Indices of classification accuracy derived from the confusion matrix used to compare mortality models (modified from Fielding and Bell 1995). Responses are classified as follows: $TP$=True Positive, $FP$ = False Positive, $TN$ = True Negative, $FN$ = False Negative.

| Index | Calculation |
|---|---|
| Prevalence | $(TP + FN) / n$ |
| Overall Classification rate | $(TP + TN) / n$ |
| Positive Predictive Power | $TP/(TP+FP)$ |
| Sensitivity | $TP / (TP + FN)$ |
| Specificity | $TN / (FP + TN)$ |
| Odds-ratio | $(TP \times TN) / (FP \times FN)$ |
| Kappa statistic (K) | $\dfrac{(TP + TN) - (((TP + FN)(TP + FP) + (FP + TN)(FN + TN))/n}{n - (((TP + FN)(TP + FP) + (FP + TN)(FN + TN))/n)}$ |
| Normalized Mutual Information statistic (NMI) | $\dfrac{-TP.\ln(TP) - FP.\ln(FP) - FN.\ln(FN) - TN.\ln(TN) + (TP + FP).\ln(TP + FP) + (FN + TN).\ln(FN + TN)}{n.\ln(n) - ((TP + FN).\ln(TP + FN) + (FP + TN).\ln(FP + TN))}$ |

**Table 3.** The final parameterized and calibrated models predicting the probability of longleaf mortality during a fire from all dataset and structure combinations. For detailed descriptions of the different model structures and datasets see text. The general form for all models is: $P(Mortality) = \dfrac{1}{1+e^{\beta}}$

| Model Structure | Dataset for Parameterization | Model # | $\beta$ |
|---|---|---|---|
| Recalibrated FOFEM | Stratified Random Subset | [1] | $0.128+2.206*BT+22.896*BT^2+0.252*SCH^2$ |
| | SCH > 0 | [2] | $0.169+5.136*BT+14.492*BT^2-0.348*SCH^2$ |
| | Complete Dataset | [3] | $-0.220-1.916*BT+30.145*BT^2+1.442*SCH^2$ |
| Modified FOFEM | Stratified Random Subset | [4] | $-1.507+4.450*SCH-4.309*SCH^2+12.788*BT$ |
| | Complete Dataset | [5] | $0.128+1.457*SCH+27.276*BT^2-0.596*Summer-0.405*Winter$ |
| | Complete Dataset | [6] | $-0.521+1.512*SCH+26.791*BT^2$ |
| RH Model | Stratified Random Subset | [7] | $-1.832+12.643*BT+3.646*RH^2$ |
| | Complete Dataset | [8] | $-1.496+6.258*RH^2+31.073*BT^2-0.659*Summer-0.407*Winter$ |
| | Complete Dataset | [9] | $-2.191+6.482*RH^2+30.076*BT^2$ |
| Complete Model | Stratified Random Subset | [10] | $-2.272+3.698*SCH-3.676*SCH^2+3.954*RH+1.242*BT+25.272*BT^2$ |
| | SCH > 0 | [11] | $0.906+25.865*BT^2-0.538*Summer$ |
| | SCH > 0 | [12] | $0.567+25.795*BT^2$ |
| | Complete Dataset | [13] | $-1.758+5.624*SCH-5.390*SCH^2+6.044*RH^2+32.456*BT^2-0.494*Summer-0.551*Winter$ |
| | Complete Dataset | [14] | $-2.427+5.512*SCH-5.228*SCH^2+6.099*RH^2+31.805*BT^2$ |

*SCH = Proportion of crown scorched (0-1)*
*BT = Bark Thickness (cm)*
*RH = Relative Humidity (0-1)*
*Summer = 1 if burned during the summer, otherwise =0*
*Winter = 1 if burned during the winter, otherwise =0*

**Table 4:** Discrimination indices calculated for the four selected model and cutoff value combinations. For an explanation of all the indices see text or table 2.

| Model # | DATASET | MODEL | Cutoff | TP | FP | FN | TN | Overall Classification Rate | Positive Predictive Power | Sensitivity | Specificity | Odds-ratio | Kappa | NMI |
|---------|---------|-------|--------|----|----|----|----|----|----|----|----|----|----|----|
| 15 | Complete | Complete - No Season | 0.4 | 303 | 154 | 281 | 4230 | 0.9124 | 0.6630 | 0.5188 | 0.9649 | 29.62 | 0.5340 | 0.7474 |
| 16 | Complete | Complete - No Season | 0.3 | 377 | 290 | 207 | 4094 | 0.9000 | 0.5652 | 0.6455 | 0.9339 | 25.71 | 0.5458 | 0.7154 |
| 17 | Complete | Complete | 0.3 | 297 | 215 | 287 | 4169 | 0.8990 | 0.5801 | 0.5086 | 0.9510 | 20.07 | 0.4855 | 0.7856 |
| 18 | Complete | RH Model - No Season | 0.3 | 363 | 301 | 221 | 4083 | 0.8949 | 0.5467 | 0.6216 | 0.9313 | 22.28 | 0.5219 | 0.7388 |

**Table 5:** Discrimination indices calculated for the best modified FOFEM model that uses the same variables currently required by the FOFEM software and the original FOFEM model (using various cutoff levels). For an explanation of all the indices see text or table 2.

| DATASET | MODEL | Cutoff | TP | FP | FN | TN | Overall Classification Rate | Positive Predictive Power | Sensitivity | Specificity | Odds-ratio | Kappa | NMI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Stratified | Modified FOFEM | 0.2 | 238 | 286 | 346 | 4098 | 0.873 | 0.408 | 0.935 | 0.454 | 9.856 | 0.358 | 0.877 |
| | Original FOFEM model | 0.1 | 584 | 4384 | 0 | 0 | 0.118 | 0.118 | 1.000 | 0 | * | 0 | * |
| | Original FOFEM model | 0.2 | 584 | 4384 | 0 | 0 | 0.118 | 0.118 | 1.000 | 0 | * | 0 | * |
| | Original FOFEM model | 0.3 | 584 | 4384 | 0 | 0 | 0.118 | 0.118 | 1.000 | 0 | * | 0 | * |
| | Original FOFEM model | 0.4 | 584 | 4382 | 0 | 2 | 0.118 | 0.118 | 1.000 | 0 | * | 0 | * |
| | Original FOFEM model | 0.5 | 584 | 4362 | 0 | 22 | 0.122 | 0.118 | 1.000 | 0.005 | * | 0.001 | * |
| | Original FOFEM model | 0.6 | 584 | 4140 | 0 | 244 | 0.167 | 0.124 | 1.000 | 0.056 | * | 0.014 | * |
| | Original FOFEM model | 0.7 | 540 | 2181 | 44 | 2203 | 0.552 | 0.198 | 0.925 | 0.503 | 12.397 | 0.165 | 0.874 |
| | Original FOFEM model | 0.8 | 61 | 581 | 523 | 3803 | 0.778 | 0.095 | 0.104 | 0.867 | 0.763 | -0.027 | 0.999 |
| | Original FOFEM model | 0.9 | 47 | 416 | 537 | 3968 | 0.808 | 0.102 | 0.080 | 0.905 | 0.835 | -0.016 | 1.000 |

**Manuscript #2: The response of longleaf pine (*Pinus palustris*) bark thickness to variation in fire regime**

**Abstract**

Bark thickness plays a critical role in defending a tree's cambium from damage by fire. Does frequent burning stimulate bark production compared to fire suppressed control? Based on data collected from an ongoing, long-term prescribed fire study, we explored differences in the bark thickness of longleaf pine trees on burned and unburned sites at different heights along the tree bole up to 200 cm above the ground. We found that relative bark thickness (bark thickness divided by diameter) at the ground level increased on burned sites compared to unburned sites, while the reverse was true at the height of between 30 and 140 cm above the ground. No difference in bark thickness was found at the height of 200 cm above the ground. We also found that bark thickness prediction could be improved by incorporating burn history as a dummy variable.

**1. Introduction**

Fire may directly affect mature trees via three possible mechanisms: (1) damage that directly hinders the photosynthate production (i.e., crown damage), (2) damage to the primary hydraulic capabilities in the stem (i.e., stem girdling or cambium damage), and (3) damage that reduces the absorption of water and nutrients from the soil (i.e., belowground or root damage). The frequent, low intensity fires typical to longleaf pine (*Pinus palustris* Mill.) communities often limit damage to tree boles, especially the lower portion of the bole, which can lead to death of the tree cambium, crippling the hydraulic architecture, and eventually resulting in the death of the tree. Over time, longleaf pine

has adapted defensive structures to better cope with these fires, and is therefore less susceptible to such damage. In contrast, few other species that grow in the region are able to withstand fires, and are, therefore, rarely able to maintain a dominant canopy position in areas where such fires are prevalent. Although adult trees of other species may be able to withstand frequent, low intensity surface fires, only longleaf pine has evolved an effective strategy of regeneration under such a fire regime. In addition to its unique adaptation of grass stage as seedlings (Boyer 1990), longleaf pine saplings have much thicker bark compared to other species such as loblolly pine (unpublished data).

The key to surviving fire damage to stem depends on protection from thick bark that insulates heat damage to cambium. Typically, bark thickness is proportional to the stem size, albeit genetic differences among species. Therefore, it has been argued that thick bark during the juvenile stage may be a better indicator of plant resistance to fire (Jackson et al. 1999). Adult trees of most species, especially when close to their mature sizes, can withstand fire damage to cambium. When fire suppression (over a long period time) allows fire sensitive species grow to their adult sizes, these species would remain as an important composition even if a natural fire regime were restored (Harmon 1984). Although some examinations have found that the varying composition of bark in different species can account for some of the difference in rates of thermal diffusion (Hare 1965, Reifsnyder et al. 1967, Gill and Ashton 1968, c.f. Martin 1963), it is generally acknowledged that the thickness of the bark is the primary determinant of the level of protection afforded to the cambium (Spalt and Reifsnyder 1962, Martin 1963, Reifsnyder et al. 1967, Ryan and Reinhardt 1988, Rego and Rigolot 1990, Ryan and Frandsen 1991).

In addition to genetic control and size influence, bark thickness may be also affected by environmental factors. For examples, Jackson et al. (1999) reported that bark thickness of pine and oak saplings differed among habitat types that likely support different fire regime; Stott et al. (1990) reported a geographic variation in bark thickness. However, little is known on whether changes in fire regime may affect the bark thickness of trees from the same population. Does frequent burning stimulate bark production compared to fire suppressed control?

The fire regime in longleaf pine forests is typified by low-intensity fires that occur at a relatively high frequency, historically every 1-10 years (Chapman 1932, Garren 1943). As a result, the damage inflicted by these fires is often confined to the lower bole. We set out to explore if the inclusion or exclusion of fire in a given stand would result in observable differences in bark thickness measurements along this section of the bole. Clear evidence of differences in bark thickness between different fire regimes could constitute evidence for a plastic response, with longleaf pine allocating more resources to defense mechanisms necessary for survival in a high fire frequency environment.

## 2. Materials and Methods

### 2.1. Data Collection

Bark thickness data was collected from the Escambia experimental Forest located near Brewton, Alabama. The data was collected from trees that are part of an ongoing study, established to examine how the season of burning affects tree growth. The study contains four biennial burning treatments (spring, summer, winter, and no burn control) and three hardwood control treatments (an one time chemical control of hardwoods in

spring 1973, periodic hand removal of hardwood stems, and an untreated control). This resulted in a total of 12 treatment combinations. Three replicate blocks were established, with each treatment combination applied to a 0.16 ha plot in each block. More detailed information on the study design can be found in Boyer (2000).

Bark thickness was measured on 5 trees from each block x treatment combination at six different heights along the bole (0, 30, 60, 90, 140, and 200 centimeters from the ground) in each cardinal direction using a Haglof Barktax bark thickness gauge and estimated to the nearest 0.05 inch. The four measurements at each height were averaged to account for variability in bark thickness. Along with the measurement of bark thickness, diameters at different positions along the bole were also measured using a diameter tape. In total, 180 longleaf pine trees were measured.

## 2.2. Data Analyses

The data collected in the field were pooled into two groups: burned (n=135) and unburned (n=45) as we were only interested in examining how the presence or exclusion of fire affects bark thickness and also to ensure that there were enough observations to perform statistical comparisons between the groups. The average bark thickness was compared between burned and unburned plots using a t-test. Since bark thickness is commonly positively correlated to stem diameter, we also used a t-test to compare the relative bark thickness (ratio of bark thickness to stem diameter at the same height) between burned and unburned plots.

Linear regression models were developed using SYSTAT (SYSTAT Software Inc.) to quantify the relationship between bark thickness and diameter at breast height (dbh). Two regression models were developed for each height along the bole; a reduced

model (Equation 1) which fits the model to all observations (both burned and unburned), and a full model (Equation 2) which incorporates a binary dummy variable ($B$) which effectively fits a separate regression line to the burned ($B = 1$) and the unburned ($B = 0$) observations.

[1]
$$BT = b_0 + b_1 DBH$$

[2]
$$BT = (b_0 + k_0 B) + (b_1 + k_1 B) DBH$$

In order to determine if there was a significant improvement in fit when the burned and unburned status was included in the regression equations, we used an extra sum of squares F-test:

[3]
$$F = \frac{SSE_r - SSE_f}{(df_r - df_f) MSE_f}$$

where SSE is the sum of squares error, df is the degrees of freedom, and MSE is the mean square error. Subscripts indicate whether the value is obtained from the reduced model (indicated by the $r$) or the full model ($f$). The critical F value was determined from an F table using $df_r$ - $df_f$ as the value of the numerator and the $df_f$ for the denominator value.

## 3. Results

Comparing the mean bark thickness values between the burned and unburned sites showed that the unburned plots had thicker bark at every level, with the differences at 0, 90, 140, and 200 cm being significant at $\alpha=0.05$ using a t-test (Table 1). When differences in stem diameter was accounted for through the use of relative bark thickness, bark thickness per unit diameter (measured at the same height) was significantly different at all heights along the stem up to (and including) 140 cm, while no significant difference

was found at 200cm.  However, in contrast to the mean bark thickness values, where unburned sites displayed thicker bark at the ground level, *relative* bark thickness was greater on burned sites at the ground level.  At heights of 90 and 140 cm, the relative bark thickness comparisons produced the same results as the mean bark thickness comparisons, with unburned sites displaying greater relative bark thickness than the burned sites. At heights of 30 and 60 cm, unburned sites had large relative bark thickness than burned sites. At the height of 200 cm, no differences in relative bark thickness was observed.

Linear regressions relating bark thickness to diameter were fit to examine if the differences found using the t-tests remained constant across the entire range of observations.  The F-tests revealed that the bark thickness and dbh relationships were different in burned vs. unburned stands at heights of 0, 140, and 200 cm up the bole (Table 2), and were more accurately described via the inclusion of a fire history term (burned or unburned).  The bark thickness-dbh relationships at heights of 30, 60, and 90 cm could be fit using the pooled data.  All regressions were significant at $a = 0.05$, although the adjusted R-squared values indicated that a large portion of the total variance in bark thickness was unexplained by dbh (Table 3).

## 4. Discussion

Given fire may affect both diameter growth and bark thickness, examination of bark thickness relative to tree diameter appears to be more informative than examining bark thickness alone.  Reduced growth rates (and therefore smaller stem diameters) have been previously reported on these same burned sites (Boyer 1987, 2000). Because bark

thickness is often positively correlated to stem diameter (Hengst and Dawson 1994, Gignoux et al. 1997, Hoffman et al 2003), it is not surprising to observe thicker bark for trees sampled on the unburned sites. However, the decreased bark thickness on the burned sites could not be simply attributed to the reduced diameter growth. Analysis of the relative bark thicknesses revealed that, at a given stem diameter, the bark at the base of the tree is thicker on burned sites, while unburned sites had thicker bark at points higher up the bole between 30 and 140 cm. Because burning may consume or char portions of the outer bark along the stem affected by flame, the increased relative bark thickness at the base on the burned site suggests that either the trees have an increased rate of bark production or bark thickness is being modified through heat-induced swelling. The increased relative bark thickness at the point higher up the bole (between 30 and 140 cm) suggests that any possible fire-induced increase in bark thickness may have been out-weighted by the reduction in the outer bark due to fire damage to the outer bark.

Fire may have two different effects on bark thickness of longleaf pine trees. On one hand, burning may char or even consume a portion of the outer bark, which tend to decrease bark thickness of trees on burned sites. This mechanism might be responsible for decreased relative bark thickness observed on burned sites at the heights between 30 and 140 cm. On the other hand, fire may inflict wound on cambium, which likely occur at the lower part of the bole (i.e., at the ground level) due to smoldering after the passage of fire front. Given the fire frequency (biennial), heating generated from flame may not last long enough to inflict cambium wounds at the bole 30 cm or above while heat generated from smoldering would only affect stem at or very close to ground level. Although an

increase in bark production due to heat stimulation or injury by fire has not been previously reported, such a 'wound response' has been observed for mechanical wounding, which has been found to increase periderm production (ie. Liphschitz and Waisel 1970). Wound response is a defensive strategy, and the individual is essentially fortifying its defenses for the next attack.

In addition to a possible increase in bark production due to wound response, the increased relative bark thickness at the ground level could also suggest that either fire may have selected against trees with thinner relative bark thickness through fire-induced mortality or bark thickness is being modified through heat-induced swelling. Fire may have selected against individuals with low bark production through fire-induced mortality. Biennial burning treatments has been applied since 1973, when the stand was ~14 years old. Trees are most vulnerable when young or in small size due to less protection from thinner bark. Those individuals producing less bark would have had higher fire-induced mortality relatively early on. We assume that there exists enough variation in bark production among individual trees within a stand . If bark production rate remain relatively constant among individuals within a stand , fire-induced mortality on the burned sites may be better explained by overall tree size or microsite conditions (i.e. fuel buildup near tree), which should not have contributed to the observed difference in relative bark thickness between burned and unburned sites.

Differences in the bark thickness could also be a physical effect resulted from bark heating. Bark swelling as a result of heating has been observed to increase bark thickness in some species up to 80%, primarily due to the expansion of the periderm (Butler et al. 2005). The variability in the observed bark thicknesses may be related to

the duration of heating during the fires.  It has been observed that expansion of the bark will continue with prolonged heating up to 20 minutes (Butler et al. 2005).  Given the burn interval (every two years), fuel accumulation and the corresponding fire intensity should remain relatively low.  Because of this, stem heating at 30cm and above may not last long enough to result in bark expansion.  Unfortunately, we have no data to reflect how the duration and intensity of heating actually compares between zero and 30 cm above the ground, or what minimum duration of heating is necessary to incur swelling. However, the lower intensity and longer duration of smoldering combustion of duff and/or other fuels would likely prolong heating at the base, possibly long enough to result in bark expansion.  At the same time, the higher intensity of heating at 30cm and above (as a result of flaming combustion) may be high enough to result in consumption of the bark, reducing the overall thickness.

Regardless of the mechanism responsible, increased bark thickness at the ground level of burned sites translates to a corresponding increase in the level of thermal protection afforded to previously burned trees.  The decreased thermal resistance at the base of the trees on unburned sites, when coupled with the increase in fuel accumulation on these sites where burning has been absent for a long period of time, equates to increased risk of girdling by fire at the base of the stem (Ryan and Frandsen 1991). Exactly how much this observed increase in bark thickness translates into increased susceptibility to fire mortality is not clear, however.  To attempt to answer this, we can apply the mean bark thickness values of the burned and unburned treatments to estimate the amount of time the tree can withstand exposure to fire before damaging the cambium, regarded as its critical residence time.  We can use a simplified version of one

dimensional heating model: $[\tau_c = 2.9x^2]$ where $\tau_c$ is the time (in minutes) required to kill

the cambium and x is the bark thickness (in cm), holding constant thermal diffusivity =

$0.06$ cm$^2$ min$^{-1}$, lethal temp is 60°C, initial temp is 20°C, and the flame temp is 500°C

(Peterson and Ryan 1986, van Mantgem and Schwartz 2003). This gives us an estimated

critical residence time at ground level of 4.18 seconds in unburned sites compared to 6.08

seconds in previously burned sites. However, we are not clear if this small difference in

critical residence time is biologically significant.

In this study, we did not have access to the stands prior to the last burn events,

and, therefore, were not able to compare pre- and post-burn thicknesses, something that

could be very informative and relatively easy to measure. It is also possible that at this

maturation stage, any mechanisms determining variation in bark thickness between

burned and unburned stands have already exerted themselves. Examination of selection

of individuals by fire when they are younger (and more vulnerable to fire damage) may

further reveal selection pressure for thick-barked individuals.

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**Table 1.** Results showing which treatment had significantly thicker bark in terms of bark thickness and relative bark thickness according to the student's t-test. Relative bark thickness was expressed as bark thickness divided by diameter outside bark.

| Bole Height (cm) | Bark Thickness | Relative Bark Thickness |
|---|---|---|
| 0 | Unburned | Burned |
| 30 | No Sig. Diff. | Unburned |
| 60 | No Sig. Diff. | Unburned |
| 90 | Unburned | Unburned |
| 140 | Unburned | Unburned |
| 200 | Unburned | No Sig. Diff. |

**Table 2.** Resultant F-values from comparing reduced vs. full models using an extra sum of squares test, and critical F-values. F-values significant at $p=0.1$ are shown in bold. Significant F-values indicate that the full model (which contained a variable distinguishing burned from unburned sites) was a significant improvement to fitting the data vs. the reduced model, which did not distinguish between burned and unburned sites.

| Bole Height (cm) | F-Value for Reduced vs. Full Model | Critical F-value ($\alpha$) |
|---|---|---|
| 0 | **6.747** | 5.59 (0.005) |
| 30 | 0.837 | 2.36 (0.1) |
| 60 | 0.225 | 2.36 (0.1) |
| 90 | 1.436 | 2.36 (0.1) |
| 140 | **2.512** | 2.36 (0.1) |
| 200 | **5.557** | 3.09 (0.05) |

**able 3.** Coefficient values for using equation 2 to predict bark thickness at a given height along the bole using $\sqrt{DBH}$ as a predictor.

| Bole Height (cm) | $b_0$ | $b_1$ | $k_0$ | $k_1$ | adj. $R^2$ |
|---|---|---|---|---|---|
| 0 | 1.4399 | 0.0805 | -1.6198 | -0.2772 | 0.2994 |
| 30 | -0.1999 | 0.3531 | 0 | 0 | 0.2522 |
| 60 | -0.1974 | 0.3312 | 0 | 0 | 0.2583 |
| 90 | -0.1124 | 0.2929 | 0 | 0 | 0.3006 |
| 140 | -1.0643 | 0.4490 | 1.0422 | -0.2030 | 0.3542 |
| 200 | -0.9726 | 0.4084 | 1.1238 | -0.2295 | 0.3320 |