Remote Sensing of Forest Health Indicators for Assessing Change in Forest Health

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Abstract

Oak decline poses a substantial threat to forest health in the Ozark Highlands of northern
Arkansas and southern Missouri, where coupled with diseases and insect infestations, it has

damaged large tracts of forest lands. Forest Health Monitoring (FHM) crown health indicators (e.g. crown dieback, etc.), collected by the U.S. Forest Service's Forest Inventory and Analysis (FIA) program, provide a method of assessing forest health. These data were obtained for the Ozark Highlands for the years 2003-2007; and levels of red oak crown dieback were calculated at the plot level along with basal area and age. Also, calculations of Normalized Difference Moisture Index (NDMI) were derived from Landsat TM imagery, annual temperature range was calculated from mean temperature data, and percent slope was calculated from a Digital Elevation Model. Quantile regression analysis was then utilized to determine the relationship between the predictor variables and red oak dieback at various quantiles of dieback. Red oak crown dieback has increased throughout the period since a low in 2004. The quantile regression analysis also indicated a difference in the relationship between the variables from linear regression estimates at higher quantiles (e.g. 90th-95th). This indicates that data at the upper tail of the distribution may point to causal relationships between variables. NDMI has the most significant relationship with red oak crown dieback although additional research is needed to determine if there is any interaction between this and other variables.

Keywords: Crown dieback, Ozarks, quantile regression

Introduction

Oak decline has posed a serious threat to the expansive forests in the Ozark Highlands. This decline has been well documented, with factors such as drought and insect infestation often being cited as the root causes (Kabrick et al., 2004; Fan et al., 2006). The United States Department of Agriculture, Forest Service (USDAFS) operates the Forest Inventory and Analysis (FIA) and Forest Health Monitoring (FHM) programs that maintain an inventory of the forest resources of the United States. The FHM program is maintained as a series of health indicators that monitor, among other variables, several measures of crown health, which allow a way to track forest health changes through time. Crown dieback is the indicator most often used to assess the overall health of a tree. This indicator is estimated visually from the ground in 5% increments of the amount of a tree's crown that has "died back" from a presumed healthy crown condition (Schomaker et al., 2007).

Previous studies have identified species in the red oak group (e.g. black oak, scarlet oak, etc.) as those being most susceptible to mortality in the Ozarks (Kabrick et al., 2008). Several variables, e.g. slope, soil depth, age, and site index, have been identified as factors associated with mortality (Oak et al., 1996). Drought has also been identified as a factor that exacerbates a reduction in crown health leading, ultimately, to an increase in mortality (Fan et al., 2011). Signs of stress in affected trees are first evident in the crown, and reflect a loss of root function or death belowground that when severe enough can lead to insect and disease attacks to the trunk; if conditions do not improve, mortality rates can increase (Barnes et al., 1998; Klos et al., 2009). Monitoring changes in crown dieback is essential in any attempt to mitigate mortality increases in the region. The use of remotely-sensed data and Geographic Information Systems (GIS) has proven useful in the detection of areas of increased crown dieback. For example, the Normalized Difference Water Index (NDWI) was utilized to map areas of increased dieback in the Missouri Ozarks (Wang et al., 2007) and to develop a risk rating to aid in the prediction of dieback based on a variety of risk factors (i.e. slope, age, and basal area) (Wang et al., 2008).

While previous studies have identified factors associated with increased levels of crown dieback and demonstrated the use of remote sensing technologies for mapping areas with increased risk, little effort has been made to identify the amount of dieback associated with changes in these risk factors. This study seeks to use variables obtained from both FIA/FHM data and derived from remotely-sensed data (Normalized Difference Moisture Index, NDMI) to assess these thresholds. NDMI and NDWI are calculated using the same ratio of near infrared and middle infrared reflectance (see Gao, 1996) and both have been used in the literature (Wilson and Sader, 2002; Wang et al., 2007). For this study, NDMI will be used as the variable name, as we attempt to assess moisture stress as it relates to crown dieback. To perform this analysis, we will employ quantile regression techniques to determine the change in quantiles of crown dieback by each variable (age, slope, basal area, average diurnal temperature ranges, and NDMI). Our objectives are to: 1) determine the level of crown dieback of species in the red oak group in the Ozark Highlands and 2) determine the relationship between the chosen variables at various quantiles of crown dieback in the region. This will further our understanding of which variables may have the greatest influence on the amount of crown dieback in the Ozark Highlands.
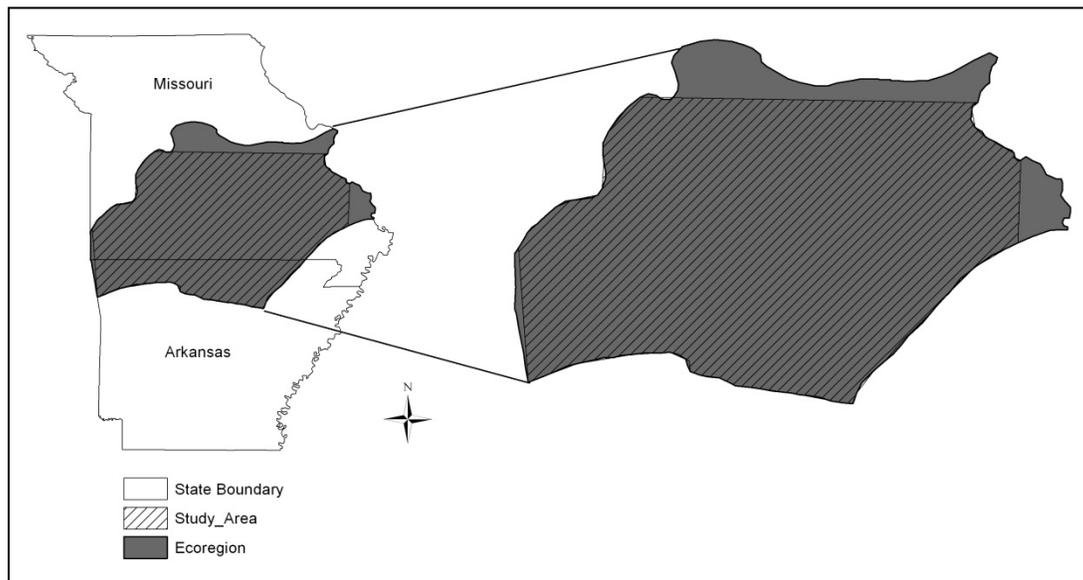

Figure 1. Map depicting the study area in the Ozark Highlands of Arkansas and Missouri.

Methods
Data were obtained from a variety of sources for variables that could be related to crown dieback. FHM data were obtained from the FIA DataMart (http://apps.fs.fed.us/fiadb-downloads/datamart.html) for Arkansas and Missouri. The Phase 3 (P3) inventory data containing crown dieback, basal area, age, latitude, and longitude were extracted for the red oak group (scarlet oak, southern red oak, cherrybark oak, laurel oak, blackjack oak, water oak, nuttall oak, willow oak, northern red oak, Shumard oak, and black oak) and for the non-red oak group (including conifers and other hardwood species) in both states and clipped to the Ozark Highlands Section, as defined by Bailey (1983) within the boundaries of Arkansas and Missouri. The study area is within the portion of this ecoregion covered by four Landsat scenes used for NDMI calculations (Figure 1). We selected data over a five year period (2003-2007); this was
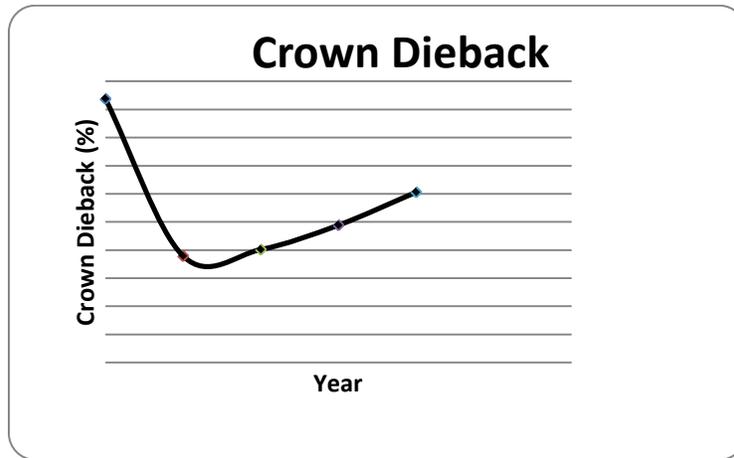
Figure 2. Temporal change of red oak crown dieback in the Ozark Highlands.

done in an effort to minimize the storage space and processing time for Landsat TM imagery. The P3 data were averaged at the plot level and exported for processing. To remove variations in estimates of red oak dieback attributed to site and stand factors, we calculated a ratio of red oak dieback and non-red oak dieback. For this calculation, we divided red oak dieback by non-red oak dieback (see Equation 1) in an attempt to signify the regional pattern of red oak dieback by using remotely sensed data (e.g., NDMI).

$$\text{Adjusted Red Oak Dieback} = \frac{\text{Red Oak Crown Dieback}}{\text{Non-Red Oak Crown Dieback}} \qquad (1)$$

Average annual diurnal temperature ranges were calculated from data obtained from the PRISM Climate Group (http://prism.oregonstate.edu, created 5 Nov 2011). Slope was calculated from a Digital Elevation Model (DEM) obtained from the National Elevation Dataset (Gesch, 2007). Landsat TM data were also obtained for the study area and NDMI was calculated for each year of the study (2003-2007). The satellite data used were all obtained in June-July of each year. The NDMI grids were then combined with the other variables utilized in the study.

Of primary concern are high values of crown dieback (e.g., those indicative of imminent mortality); for this purpose, quantile regression was chosen (Equation 2). Quantile regression, first developed by Koenker and Bassett (1978), is used to estimate the conditional quantiles of a variable of interest (i.e., adjusted red oak dieback ratio) on a set of contributing/limiting factors, providing a more thorough analysis of the relationships between the variables (age, diurnal temperature range, basal area, % slope, and NDMI), where a change in a given quantile is estimated by the change in red oak crown dieback produced by changes in predictor variables. Data were processed in R Statistical Software utilizing the quantreg package (Koenker, 2008).

$$y_i = \beta_0^{(p)} + \beta_1^{(p)} x_i + \varepsilon_i^{(p)}, \tag{2}$$

where:
y_i = the estimated conditional quantile of crown dieback;
p = the chosen quantile;
β = parameters of the variables in the chosen quantile;
ε = error term for each quantile.

Results and Discussion

The average amount of annual crown dieback decreased from 2003 to 2004, following a recovery from a severe drought that impacted the area in years prior to 2003 (Fan et al., 2006). Since 2004, there has been a steady increase in the amount of crown dieback found in the Ozark Highlands (Figure 2). The results presented in this section will explore the variation in crown dieback at various quantiles in an attempt to understand the relationships between various factors impacting the red oak forests in this area.

We present plots of the intercept and coefficients for each of the five covariates utilized in this study (Figure 3). From this figure we can see the changes in the effect of each covariate at each quantile. Where the quantile regression estimates are outside the confidence interval of the least squares estimate, significant differences occur at that quantile. This indicates that, at those quantiles (e.g. 95th), for given variables, a causal relationship with red oak crown dieback exists (see Cade et al., 1999; Hao and Naiman, 2007). The analysis in this study utilized various quantiles to determine where these causal factors may exist, which may have been missed by simply using least squares regression (Cade and Noon, 2003). For age, we can see that the least squares estimates poorly represents the relationship in the upper (95th) quantile as the quantile regression estimate is outside the confidence interval of the least squares estimate. For temperature range, there is little difference between the least squares estimates and the estimates at each quantile. There is a slight increase in crown dieback as the temperature range increases, and a steep incline in this rate at the 90th quantile but all estimates stay within the confidence interval of the least squares estimate. There is a slight effect of basal area on crown dieback at the 95th quantile. This could indicate that highly stocked stands have more of an impact on crown dieback in red oaks. Percent slope exhibited no difference with least squares estimates at any quantile. NDMI was outside the confidence interval for the least squares regression estimates at nearly every quantile with the most significant difference at the 95th quantile.

To assess the impact of each variable on red oak crown dieback, the 5th, 25th, 50th, 75th, and 95th quantiles will be used (Table 1). Age generally has a negative relationship with crown dieback, particularly between the 75th and 95th quantiles. We can also observe from the graphical representation (Figure 4) of these quantiles that the variation is greatest between the 75th and 95th quantiles. There is also a change in slope between the 25th and 50th quantiles and 75th and 95th quantiles indicating that there are differing rates of change between the upper and lower 25% of crown dieback across the range of stand ages found in the Ozarks. This disparity could be explained by younger trees allocating more energy to root production and older stands allocating
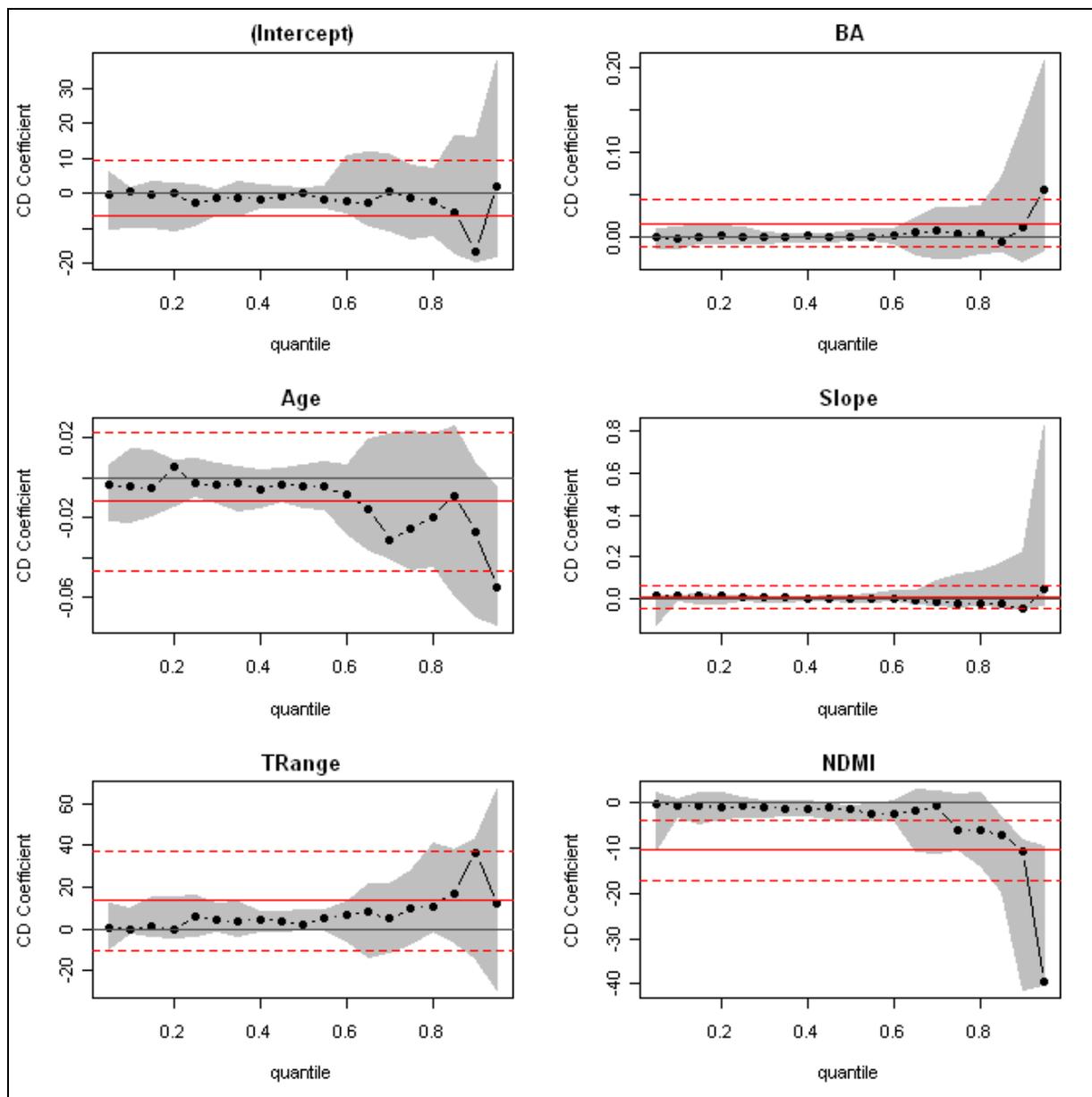
Figure 3. Change of the intercept and partial slope with estimated conditional quantiles for all Variables predicting crown dieback (CD). In each plot, the solid red line represents the least squares regression line; the dashed red lines represent the 95% confidence interval of the least squares regression. The black dots are estimates at each conditional quantile and the gray areas the 95% confidence interval for the quantiles. The variable names are: BA = Basal Area; Age = actual tree age; Slope = % slope; TRange = mean annual temperature range; and NDMI = Normalized Difference Moisture Index.

Table 1. Coefficient estimates for the mean-based and quantile regressions.

Variable	Linear Regression	Quantile Regression				
		5th	25th	50th	75th	95th
Intercept	-9.4432	-0.2912	-2.7920	0.2117	-1.2050	2.0533
Age	-0.0118	-0.0033	-0.0028	-0.0039	-0.0256	-0.0544
TempRange	15.2314	0.7751	6.0072	2.1180	9.8913	11.8015
Basal Area	0.0124	-0.0003	-0.0003	-0.0002	0.0035	0.0565
Slope	0.0067	0.0143	0.0048	0.0011	-0.0225	0.0453
NDMI	-10.9730	-0.0063	-0.6879	-1.3068	-5.9249	-39.6837

energy to shoot development (Barnes et al., 1998) for low and high levels of crown dieback. For moderate levels of crown dieback in red oaks, there could exist some interaction between age and other variables, as discussed by Wang and others (2007).

The annual temperature range proved to be an interesting variable as all selected quantiles were below the coefficient estimate of the linear regression; closer inspection will reveal that this does not hold true for the 85th – 95th quantiles. Figure 3 shows this change and the general trend of crown dieback increasing with an increasing average annual temperature range. The upper 5% of the data exhibit the greatest variation and steepest rate of change between crown dieback and temperature range (Figure 5). This indicates that higher levels of crown dieback could be associated with wide ranges in average annual temperatures (e.g. an unusually hot summer or cold winter). The coefficients for basal area show the greatest difference between the 75th and 95th quantiles. The change in the slope between the 75th and 95th quantiles (Figure 6, Table 1) indicate an increase in the effect of basal area on crown dieback in the upper quantiles. Here, more densely stocked stands would have more competition for resources than those in less dense stands.

Generally speaking, crown dieback levels were higher on sites with steeper slopes. However, slope exhibited little variation across all quantiles examined and did not vary outside the confidence intervals of the least squares regression. The only change occurs, as with other variables, between the 75th and 95th quantiles where the indications are that lower slopes have greater crown dieback (Figure 7) but again, these estimates do not vary far from the linear regression estimates. For NDMI, the coefficient estimates are negative at each quantile (Table 1) indicating that lower NDMI values are associated with higher crown dieback, which could be attributed to a lack of available moisture. For quantiles above the 25th (Figure 8), there is a negative trend in the data. While this trend is captured by the linear regression coefficient, the upper quantile (above 75th) shows a large departure from that estimate. This indicates that for high levels of crown dieback, NDMI may be useful for delineating red oak dieback from dieback evident in other species. For these reasons, NDMI was the most significant variable in our analysis. This reinforces previous studies that found that drought can cause water stress in forests and decrease in crown health leading to mortality (Fan et al., 2006; Wang et al., 2007).
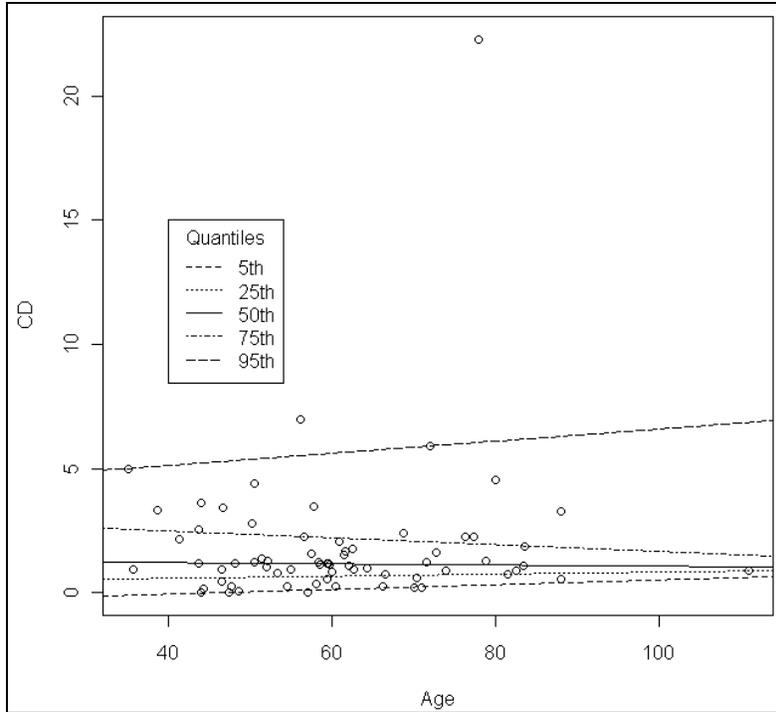
Figure 4. Graph of red oak crown dieback (CD) and Age (in years) with the 5th, 25th, 50th, 75th, and 95th quantiles depicted.
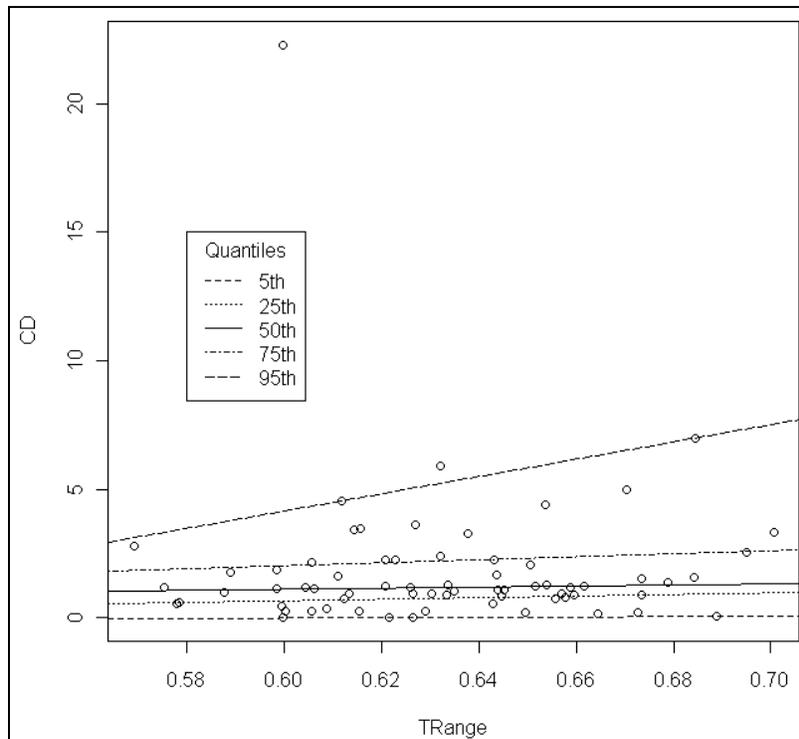

Figure 5. Graph of red oak crown dieback (CD) and mean annual temperature range (TRange) with the 5th, 25th, 50th, 75th, and 95th quantiles depicted.
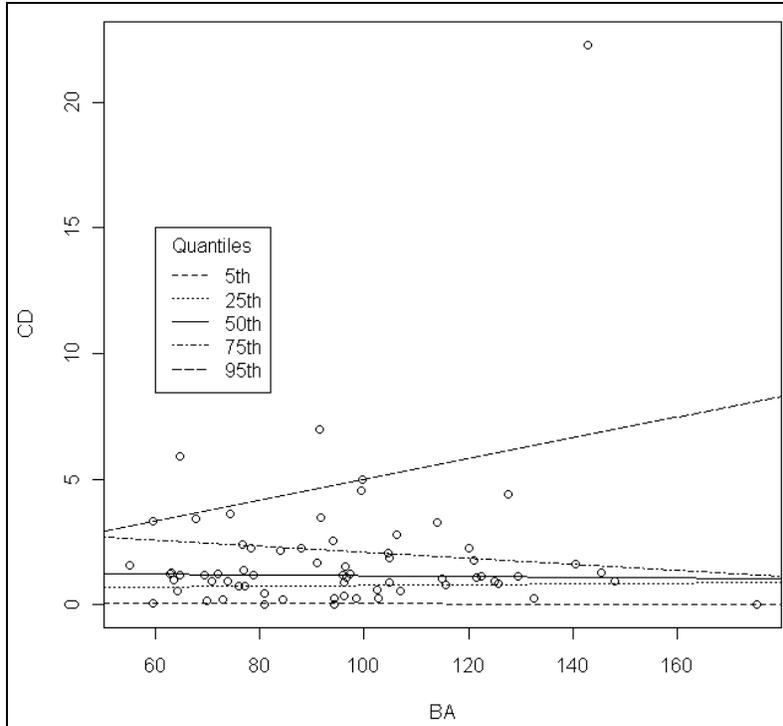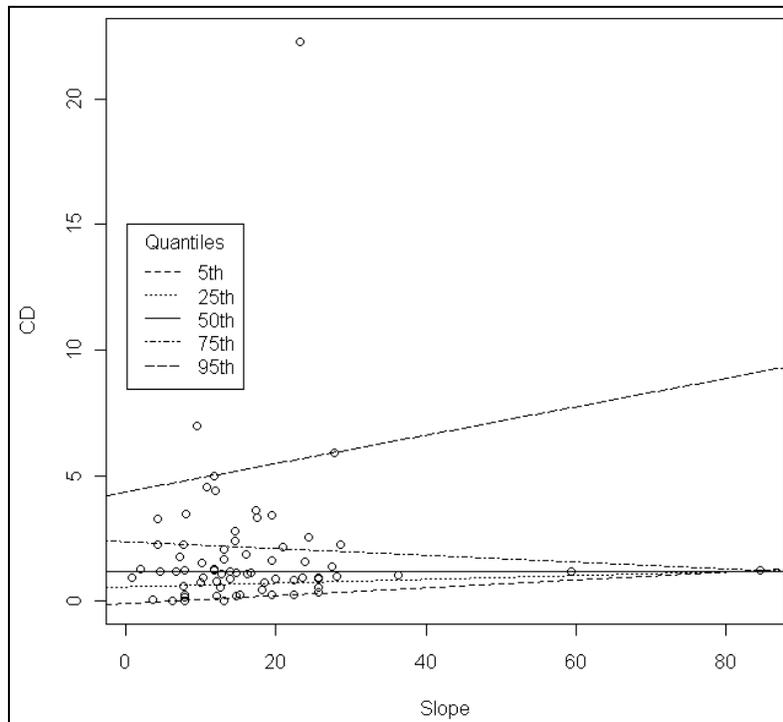
Figure 6. Graph of red oak crown dieback (CD) and basal area (BA) with the 5th, 25th, 50th, 75th, and 95th quantiles depicted.

Figure 7. Graph of red oak crown dieback (CD) and % Slope with the 5th, 25th, 50th, 75th, and 95th quantiles depicted.
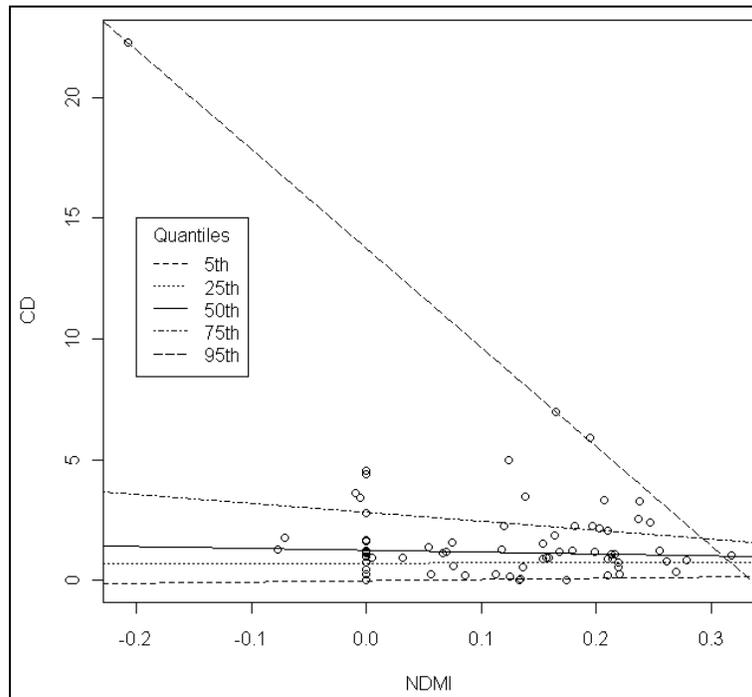
Figure 8. Graph of red oak crown dieback (CD) and Normalized Difference Moisture Index (NDMI) with the 5th, 25th, 50th, 75th, and 95th quantiles depicted.

Age, basal area, and NDMI had quantile regression estimates outside the confidence intervals for least squares regression. These variables can be used to further refine models to predict crown dieback across the Ozark Highlands. Also, all variables exhibited the greatest variation between the 75th and 95th quantiles. This suggests that the effects of these variables are not constant across the distribution of crown dieback in red oak species.

Conclusions

Changes in crown dieback in red oak species in the Ozark Highlands at various quantiles have been presented. This was done in an effort to determine the impact of the chosen variables on predicting crown dieback and to determine those variables that have changing relationships at higher/lower values of crown dieback. We have found that at higher quantiles (e.g. 75th to 95th), there tends to be larger variation between crown dieback and predictor variables. Cade et al. (1999) found that barring any immeasurable interactions between variables, the upper quantiles should be parallel. Our results indicate there could be some interaction among the variables which could indicate that a non-linear model may better serve as a means of predicting crown dieback.

The variables utilized in this study could be obtained as spatial datasets or, in the case of NDMI, derived from remotely-sensed data. While the goal of assessing the impact of each variable on crown dieback was met, we feel that additional efforts should be undertaken to determine an appropriate model for predicting crown dieback based on the variables that lead to the highest

percentage of crown loss. This could provide a more robust means of predicting crown dieback in the future. Our study only considered FHM data over a five year period, which lead to a reduced sample size, possibly influencing variable coefficients at changing quantiles. Future inventory cycles will increase the number of samples available for model development. Additional research efforts will focus on the development of models to assess crown dieback in red oak and other species, which could serve as valuable tools for developing a means of monitoring weather and climate effects on forests in the Ozark Highlands.

Acknowledgements

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