Improving Site Quality Estimates in the Upland Hardwood Forests of the Southern Appalachians with Environmental and Spatial Modeling

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ABSTRACT

In the upland hardwood forests of the southern Appalachians, management tools are needed based on the characteristics of the site to quantify the site quality where no accurate maps of site quality exist. Three studies were conducted to achieve this objective. The first study tested if independent measures of forest productivity, based on vegetation and environment, in a six-county study area in the Blue Ridge Mountains in North Carolina would correlate with measures of forest productivity obtained from U.S. Forest Service Forest Inventory Analysis (FIA) data. Specific hypotheses included: FIA measures of forest productivity are related to one another; FIA measures of forest productivity are related to FIA-measured landscape parameters; and FIA measures of forest productivity are related to independent measures of forest productivity based on landscape parameters and soil characteristics. Four predictive indices of forest productivity were used; three were generated in a geographic information system (GIS). FIA measures of forest productivity were not significantly correlated to FIA measured landscape parameters. FIA site productivity classes were significantly correlated to FIA measures of site index. Independent measures of forest productivity, particularly the Moisture Regime Index (MRI) and the Forest Site Quality Index (FSQI), were significantly correlated to FIA measures of site index. Topography can be used to delineate site quality, but the addition of soil depth can prove to be useful in the estimation. The second study was designed to develop methods, based on field and digital data, to identify colluvial soils in the central Ridge and Valley of southwestern Virginia. Two hypotheses were tested. First, on the linear side slopes of the study area, where site quality is low in stands with subxeric to xeric moisture regimes, vegetation and topography can indicate colluvial soils. A second hypothesis tested if the topographic signature of colluvial soils could be identified geospatially with a digital elevation model. Results indicated that the MRI and the Terrain Shape Index predicted the presence of colluvial deposits in the study area. The basal area of yellow-poplar was positively associated with colluvial soils. A GIS-based model found the slope difference of colluvial soils to be less steep than residual soils as the size of the neighborhood increased. The final study determined if measures of site quality in the Blue Ridge Mountains of North Carolina were related to the water budget. Specifically,the hypothesis that site index could be predicted by variables that represented the inputs, usage, and supply of water was tested. A second hypothesis questioned if site quality classes could be predicted by a combination of topography and the annual water budget. Regression models predicted site index to be a function of topography, available water supply, and the annual water budget, but the accuracy was low (R^2=0.11 and 0.13). A classification approach yielded better results. Incorporating the annual water budget into the FSQI increased classification accuracy of predicted site index by 50%, and decreased the number of sites misclassified by one class by 8%. Where accurate maps of site quality do not exist, the MRI, the abundance of yellow-poplar, and the modified FSQI may be used to delineate site quality for site-specific management and, ultimately, greater return on investment for the landowner.

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Chapter 1

Introduction and Review of Literature

1. Context and Justification

To properly manage a forest it is essential to classify, map, evaluate, and interpret the resource. Avery and Burkhart (2002) defined site as an area in which trees grow, and stated that the environment of the site determines the type and quality of the vegetation potential. Site quality is a measure of potential productivity. Site can be expressed indirectly through the local climate, topography, soils, and vegetation present, and directly by growth of trees (Helms, 1998; Johnson et al., 2002).

Forests are usually managed for multiple benefits that include timber production, wildlife habitat, recreation, and aesthetics. Management efforts for timber production need to be focused on forested land of high site quality, because timber quality and quantity are directly related to site quality. Forests formerly used for timber products are being converted to other uses. As a result, site-specific forest management is needed where sites best suited for timber production are identified and managed intensively (Sedjo and Botkin, 1997). Methods to accurately identify site quality must be improved so that sites with the highest potential productivity can be identified and mapped. If these sites receive the most intensive management, sites better suited for other purposes, such as water protection, wildlife habitat, recreation, or wilderness can be managed to optimize these values. This could increase the efficiency with which we utilize our forests and reduce the commercial land base used for timber production.

Site quality is most commonly estimated from site index (SI), which is based on the measured total height of a tree at a designated age, typically 50 years for eastern hardwood species. Unfortunately, SI may not accurately estimate site quality in the southern Appalachians. Using SI, the selected trees must have been in a dominant or codominant crown class their entire life, have no damage to the apical meristem, and be free from damaging agents that affect growth. Because of the disturbance history in the hardwood forests of the southern Appalachians, these assumptions are seldom met. The validity of SI as a measure of site quality also relies on

the assumption that height growth is independent of stand density. Recent research has demonstrated that this assumption may not be valid (MacFarlane et al., 2000).

Evaluation of site quality in mountainous terrain is a challenge. The upland hardwood forest ecosystems of the southern Appalachians are some of the most complex and diverse in North America due to the combination of topography, geology, climate, and soil found throughout the region. These attributes lead to a wide range in site quality and productive capacity across the region, driven largely by climatic and topographic controls on water availability (Smith, 1994). Because accurate estimates of site quality do not exist in most of the Appalachians, management tools are needed that are based on the characteristics of the site to quantify the site quality.

2. Objectives and Hypotheses

In response to this issue, three studies have been conducted in the upland hardwood forests of the southern Appalachians with an overall objective to develop management tools that can accurately delineate site quality based on the potential of the environment. Specific questions for each study were as follows:

Predicting Upland Hardwood Site Quality in the Southern Appalachians using FIA Data and Geospatial Modeling

Within Forest Inventory and Analysis (FIA) plots in a six-county area of the Blue Ridge in western North Carolina:

1. Are FIA measures of forest site quality related to one another?
2. Are FIA measures of forest site quality related to FIA-measured landscape parameters, such as aspect and slope?
3. Do independent indices of forest site quality, based on topography and soil attributes, relate to FIA measures of forest site quality?

Identifying Colluvial Soils in the Ridge and Valley to Refine Measures of Upland Hardwood Site Quality in the Southern Appalachians

On the sideslopes of mountains in the central Ridge and Valley in southwestern Virginia:

1. Can vegetation and topography be used as indicators of colluvial soils and deposits?
2. Can colluvial soils and deposits be predicted according to their topographic signature with a slope change algorithm using a Digital Elevation Model?

Predicting Upland Hardwood Site Quality in the Southern Appalachians as a Function of the Inputs, Supply, and Usage of Available Water

Within Forest Inventory and Analysis (FIA) plots in a six-county area of the Blue Ridge in western North Carolina:

1. Can FIA measures of SI be predicted by the inputs, supply, and usage of available water?
2. Are site quality classes related to topography and the annual water budget?

These three studies were designed to provide management tools to land owners to accurately quantify the site quality of their forests, where no accurate measures exist. This should lead to more efficient management practices, better economic return, and ultimately, ecologically sustainable timber production.

3. Literature Review

The concept of forest site quality

Forest site classification has been a topic of active research in the United States since the early 1900's, when silvicultural concepts began to be applied to the nation's forests in order to manage the resource. Early on, scientists conducted extensive research in order to predict the yield of managed forests (Bates, 1918; Frothingham, 1918; Watson, 1917). From these investigations emerged the SI, an index of site quality based on the total height of a tree at a designated age, which is typically 50 years for eastern hardwood species. This method has been the standard by which many softwood and hardwood forests have been evaluated for site quality. Over time, limitations to the use of SI emerged and other methods were proposed, particularly those based on the environment of the site. Methods to quantify site quality have gone from basic observations of tree growth to multifactor analyses (Carmean, 1975).

Approaches to estimating site quality have been grouped into two broad categories: direct methods, or those that assess site quality based on the plants of the site, and indirect methods, those that assess site quality based on the environment of the site. Within the past 20 years the development of geospatial analysis has allowed site quality research to expand the scope of analysis. Before this technology, foresters had to conduct inventories by extensive fieldwork in order to quantify the environment and productivity of their land. However, the advent of geospatial analysis has shown potential to increase the efficiency of site quality measurement, and continues to be an effective tool to push the science forward.

Direct methods of measuring site quality

Site Index

Direct methods of site quality estimation include SI and vegetative indicator species. This group of methods is based on the presence or measurement of particular species that indicates certain growth characteristics about a forest (Carmean, 1975). A method that has endured is the SI, summarized and introduced from previous efforts by Frothingham (1917). Site Index is estimated using the average height of dominant and codominant trees growing in a well stocked, even-aged stand at a given index age (typically 50 for eastern hardwoods) expressed in

feet or meters. Ideally, the benefits of using SI to evaluate a forest include its relation to site productivity, its ease of measure, and its independence from stand density (McQuilkin, 1989).

Limitations arise when the land-use and disturbance history of the site has produced an inferior and unrepresentative stand of trees, when there are no suitable trees for measurement, and when the stand contains multiple species and ages of trees. The main drawback to using SI is that it requires the user to accept a number of underlying assumptions that usually are not known for the stand being measured (Beck and Trousdell, 1973). Assumptions that are most difficult to assess include uniform site quality, unsuppressed and undamaged measurement trees, and a uniform or even-aged stand (McQuilkin, 1989). The methods that have been used to create the standard SI curves have assumptions and limitations as well. Different age classes may be unequally represented in a SI curve (Carmean, 1975). Barnes et al. (1998) reported that harmonized growth curves did not accurately represent actual stand growth curves, and that SI ranges need to be equally represented at all ages, which may not be feasible due to harvesting or other land practices. SI also assumes that the growth rate is proportional at all ages and for all qualities of sites, which is not the case (Beck and Trousdell, 1973). Another concern about SI is the broad area, typically a region, for which SI tables are used, such as the SI curves for upland oaks in the central states developed by Carmean (1971). Site indices such as these fail to adequately represent sub-regional or site specific nuances of more discrete areas. Others have discredited SI because it is difficult to confirm that a stand has not been influenced by stand density or land-use history (Berguson et al., 1994; Monserud, 1984). Past land-use activities and disturbances on the forested landscape, such as high grading, clear-cutting, site preparation, and invasive pests and diseases, have been shown to significantly affect species composition and site quality in the southern Appalachians (Brashears et al., 2004; Elliott et al., 1997; Ellison et al., 2005). The forests of the central and southern Appalachians frequently experience ice storms, which have affected the distribution of tree species across the landscape (Mou and Worrillow, 2000). Research has shown that different tree species vary in their susceptibility to ice storm damage according to topographic position (Worrillow and Mou, 1999). This type of natural disturbance can cause the tops to break out of trees, which would prevent the use of the SI in these stands.

Indicator species

Forest managers have historically associated certain individual tree and herb species with site conditions that have particular moisture, fertility, and temperature regimes (McNab et al., 2002). Using indicator species and species groups to determine site quality has its roots in the work of Cajander (1926), who devised a system of five vegetation classes composed of various site types based on ground vegetation indicator species for the forests of southern Finland. Fundamental to this system is the presence of species with limited ecological adaptations, the principle being representation of a unique niche (Cajander, 1926). McNab et al. (2002) found this approach to be useful in the southern Appalachians to predict site quality. In the mountains of western North Carolina, it was determined that the presence of white ash (*Fraxinus americana* L.), yellow-poplar (*Liriodendron tulipifera* L.), black cherry (*Prunus serotina* Ehrh.), and black locust (*Robinia pseudoacacia* L.) indicated highly productive sites, while scarlet oak (*Quercus coccinea* Muenchh.) and northern red oak (*Q. rubra* L.) among others, were found on plots with significantly lower productivity (McNab et al., 2002). For example, white ash occurred on 71 plots (out of 559 total plots) at an elevation range of 518 to 1378 m; the mean annual increment basal area of plots that contained white ash was 22% higher than that found in plots without this species ($p = 0.007$) (McNab et al., 2002). Similar research (McNab et al., 2004) concluded that the presence of chestnut oak (*Q. prinus* L.) and American holly (*Ilex opaca* Aiton) increased the probability that a subject plot was situated in the southern zone of the Cumberland Plateau, while the presence of yellow-poplar, short-leaf pine (*Pinus echinata* Mill.), and eastern white pine (*P. strobus* L.) indicated a high probability of being in the northern zone of the plateau.

More recently, the moisture regime index (MRI) has shown promise in delineating site quality of the upland hardwood forests in the southern Appalachians (McNab and Loftis, in press). The MRI is an expert knowledge system that is based on the presence of tree species to determine site quality. Groups of tree species are known to occur together across the forested landscape due to similar site requirements (Smith, 1994; Eyre, 1980). The underlying premise of the MRI may be found in the environmental gradient work of Whittaker (1956). Tree species in the southern Appalachians respond to gradients of temperature and moisture, and from this observation, four classes of soil moisture were determined to exist in the mountains: mesic, submesic, subxeric, and xeric (Whittaker, 1966). Each of these soil moisture classes was

assigned an index weight, with the higher index numbers indicating greater moisture. Based on plots across the Great Smoky Mountains, commonly occurring hardwood and conifer species were evaluated to determine their site requirements, particularly moisture and elevation. From these observations, each species was assigned to a moisture class based on where it occurred most frequently. For each plot, the weighted average of all trees' index values was used to determine the site quality. Whittaker (1966) found the index to be highly correlated to forest productivity across a wide environmental gradient in the Great Smoky Mountains.

McNab and Loftis (in press) conducted a similar experiment in Bent Creek Experimental Forest, located outside of Asheville, NC, using point data from field plots. The primary difference between the two approaches is that Whittaker (1966) considered the density of each species in his final calculation whereas McNab and Loftis (in press) considered only the presence or absence of each species. It has been reported that the density of some species may be more of a reflection of recent disturbance than of available moisture across the landscape (Beck and Hooper, 1986; McGee and Hooper, 1975). In response to this, McNab and Loftis (in press) designed their study to account for this potential source of error by assessing the presence or absence, and not the density of a species. Potential values for the MRI may range from 0 to 4, with 4 being the most mesic.

Ecological species groups include plants that repeatedly occur together in areas with similar physical conditions, and the species within a group are assumed to have similar site preferences. These groups represent a multivariate gradient of abiotic and biotic site conditions, and the power of prediction lies with the group members as a whole, and not in individual values assigned to each species. This technique has been used to map ecosystem types in old growth forest in Michigan (Simpson et al., 1990), in disturbed hardwood forests in southern Michigan (Archembault et al., 1990) and in disturbed hardwood forests in Wisconsin (Hix, 1988).

In the western and northern United States, habitat-type classification (Kotar et al., 1988; Pfister and Arno, 1980) has been useful in managing forested federal lands. Areas of similar climax vegetation (plant associations) are identified rather than ecosystem type. The rationale of

habitat types is similar to that of ecological species groups in that they collectively represent the landscape components that support the same primary climax vegetation (Alexander, 1986).

The use of indicator species to assess site quality is not without its criticisms. The indicator species approaches to site quality described above have proved useful in structurally simple systems, but limitations arise when complex and disturbed ecosystems are encountered (Rowe, 1962). In the southern Appalachians, most of the forests have been continuously disturbed by disease or logging since the late 1800's, and the vegetation that appears on a landscape in "distinct" groups may or may not be representative of the true productivity of the site. Further, the classification of the ecological species groups and habitat types are largely subjective and rely heavily on the judgment and knowledge of the observer and user (Rowe, 1962). Finally, vegetation may be lacking due to chance or historic causes (Barnes et al., 1998).

Indirect methods of measuring site quality

Approaches to site quality estimation based on the environment of the site focus on how these characteristics affect available water and nutrients for vegetation growth. Topography, soil, geology, and climate are the drivers of site quality in this group of approaches. It is difficult, if not impossible, to decouple the effects of these variables from one another, which is likely why the question of site quality endures. This issue is reflected in the studies included in this review. It is hard to categorize the results, since they could simultaneously go into multiple categories.

The influence of topography

Topographic variables, particularly elevation, aspect, slope percent, slope position, and slope shape have been cited to be predictors of site quality because of their influence on the site moisture regime (Carmean, 1979). It has been asserted that available moisture for plant growth, which is directly related to these variables, is the single most important factor that drives site quality and productivity in the southern Appalachians (Smith, 1994). Whittaker (1956), and later Golden (1981), reinforced this idea and described the forested communities of the Great Smoky Mountains through elevation and moisture gradients. Day and Monk (1974) also followed this logic when they concluded that a soil moisture gradient influenced species distribution at

Coweeta. Braun (1950) wrote one of the first comprehensive surveys of the deciduous forests in eastern North America, and described them in terms of topography, soils, and microclimate. In the Ridge and Valley, the Forest Site Quality Index (FSQI) (Meiners 1982, 1984) is a simple and easy-to-use method that describes site quality and productivity based on aspect, slope position, and slope percent as they influence available soil moisture. The FSQI is useful in the Ridge and Valley, but its use is limited to areas in which there are slopes in excess of 10% over uniform parent material (Meiners, 1982). Muller (1982) found a strong correlation between aspect and the distribution of shagbark hickory [*Carya ovalis* (Wangenh.) Sarg.], bitternut hickory [*C. cordiformis* (Wangenh.) K. Koch], and mockernut hickory [*C. tomentosa* (L.) Nutt.] in the mixed mesophytic forests of eastern Kentucky. Significant differences in growth were found in yellow-poplar, chestnut oak, and red maple (*Acer rubrum* L.) growing on northeast versus southwest slopes (Fekedulegn et al., 2003). In the northern hemisphere, slopes with an aspect of north to northeast have higher moisture levels versus slopes with an aspect of south to southwest due to the higher amount of solar insolation incurred by the latter (Iverson et al., 1997). Fekedulegn et al. (2004) found that north and east aspects were 27-50% more productive than west and southwest aspects with regard to hardwood volume. The differences in that study were driven by differences in microclimate between the cooler and warmer aspects, particularly temperature and humidity. McNab (1991) found elevation, aspect, slope gradient, and indexes of landform to account for 97% of the variation in forest types in Bent Creek Experimental Forest, which is within the study area. In the Ridge and Valley, Lipscomb and Nilsen (1990) found that rhododendron (*Rhododendron maximum)* was most abundant on lower northeast slopes, and that mountain laurel (*Kalmia latifolia)* was most abundant on southwest slopes.

Studies of forest productivity commonly analyze pattern or process, or infer one from the other. For example, elevation is often cited as a significant topographic predictor of site productivity and species distribution due to its relationships with precipitation and temperature. There is generally an increase in precipitation and decrease in temperature as elevation increases (Lookingbill and Urban, 2004). McCay et al. (1997) reported a strong relationship between the distribution of secondary forests in eastern West Virginia and elevation. Bolstad et al. (2001) stated that the leaf area index was a function of elevation and terrain position in the mountains of North Carolina. Elevation and a fertility gradient were found to be the main predictors of old

growth deciduous forests in eastern Kentucky (McEwan et al., 2005). While the studies cited have contributed greatly to the understanding of site quality in relation to topography and available water for tree growth, it is important to remember that elevation differences do not cause the distribution of forest species. Rather, the climatic variables that co vary with elevation, i.e. precipitation and temperature, are the influences that affect forest species distribution (Lookingbill and Urban, 2005).

An understanding of landform is essential to understanding the distribution of vegetation in the southern Appalachians (Parker, 1982). Landform affects water availability through its shape, geology, and amount of protection by influencing solar radiation and moisture retention (Rowe, 1984). Smalley (1984, 1986) made a significant contribution to this literature by developing a hierarchical and comprehensive landform classification system for the Cumberland Plateau and Cumberland Mountains. The system recognizes numerous land types found in the region and describes the associated geology, soils, water, vegetation diversity and productivity, management problems, and optimal species for the growing conditions for each land type (Smalley 1984, 1986). Smalley's work was and still is very pertinent; however, his method was subjective and did not include any modeling efforts, which would allow land managers to predict future growth and yield and guide silvicultural activities in a more concerted way.

McNab (1989; 1993) developed a terrain shape index (TSI) as well as a landform index (LFI), which quantified the microscale and mesoscale variation, respectively, among landforms and their effects on site productivity in the Blue Ridge. The LFI quantifies slope position (ridge, side slope, and cove), to which McNab (1993) was able to correlate yellow-poplar SI (p = 0.45–0.65). The TSI provides a measure of the concavity or convexity of the landform on which a plot is located. Hack and Goodlett (1960) originally suggested that landform modified the way water moved across the forested landscape, which in turn was related to the distribution of forest vegetation in the southern Appalachians. It was this premise that inspired the creation of the TSI (McNab, 1989). Defined as the mean relative difference in elevation between the center of a plot and its boundary, the TSI was originally devised as a field tool (McNab, 1989). Positive values indicate a convex, or water-shedding landform (ridges, spur ridges, nose slopes), and negative values indicate a concave, or water-holding landform (creek beds, coves, bottoms). The original

development of the model related the TSI to yellow-poplar SI in the Blue Ridge.

The influence of soil

Site quality has often been related to the physical properties of soil, particularly the soil water holding capacity, which is influenced by depth and texture, among other things. Callaway et al. (1987) found that soil water holding capacity influenced the discrimination of twelve forest types in Great Smoky Mountains. Fralish (1994) reported a decrease in hardwood basal area and SI with a decrease in soil volume for water storage. Where shallow soil profiles exist a decrease in the soil water storage is especially significant to forest productivity (Childs et al., 1986). Baker and Broadfoot (1979) created a field classification for several commercially important southern hardwoods based on the physical, moisture, nutrient, and aeration properties of the soil to assess the potential productivity of a site. Jones (1987) stated that it was too difficult to distinguish between the very best and other levels of site quality based on stand and tree measures alone. As a result, Jones and Saviello (1991) developed a way to determine site quality for hardwood growth based on slope position and soil characteristics, such as texture, stoniness, and depth. More recently, Iverson (1997) developed a GIS-driven integrated moisture index (IMI), based on flow accumulation, curvature, hillshade, and the total water holding capacity of the soil, that explained 64% of the variation found in upland oak SI within stands on the Allegheny Plateau.

The soil moisture gradient has long been recognized for its influence on the spatial variability of site quality, species composition, and forest growth. Whittaker (1956) and Day and Monk (1974) found that elevation and topography, proxies of the soil moisture gradient, explained the vegetation patterns in the mountains of western North Carolina. White (1958) reported that the amount of soil moisture was the primary influence on any estimate of site productivity. Other studies have found that soil water-holding capacity and local topography can be used to explain differences in forest composition and site quality (Stephenson and Mills, 1999). Carmean (1979) stated that soil, topographic, and climatic attributes could indirectly estimate site quality over large landscapes independent of the vegetation cover. The soil attributes he cited as influential were those that affected the amount of water the soil could hold, such as depth, texture, and stone content. Elliott et al. (1999) described soil moisture as a

function of precipitation, terrain shape, and soil characteristics. Topography and soil storage were found to be the primary controls on hillslope soil moisture during dry periods in the southern Appalachians (Yeakley et al., 1998).

The influence of geology

One element that has not been extensively analyzed in the search for site quality estimation is bedrock geology and its effect on soil fertility. While it is likely true that site quality differences within a physiographic province are primarily influenced by available moisture, differences among physiographic provinces may be distinguished by, among other things, bedrock geology and the fertility of the soils it produces. Available moisture, available nutrients, and the pH of the soil work in concert to produce the fertility of a soil available for plant growth (McBride, 1994). In a very early study, Cowles (1901), for example, recognized the influence and importance of geology on soil development and topography, and the effects they produced on the vegetation patterns. Bedrock geology and stream nitrate levels in mid-Appalachian hardwood forests (PA, MD, and WV) were related significantly to soil pH, soil exchangeable Ca, and the presence of white ash, sugar maple (*A. saccharum* Marsh.), and eastern hemlock [*Tsuga canadensis* (L.) Carriere] (Williard et al., 2005). Two of these three species are typically viewed as high fertility indicator species (white ash and sugar maple). Burger (1995) recognized the contribution of bedrock and surficial geology to fertility gradients at the Fernow Experimental Forest. Additionally, a classification of geologic formations that contribute to soil fertility was recently included in an ecological classification scheme for mountainous terrain in western North Carolina (Simon et al., 2005).

The influence of climate

Climate has been found to significantly affect the distribution of tree species, but the scale has to be sufficiently large for this variable to have an effect. For example, Holdridge (1947) developed a classification scheme of the global distribution of plant biomes as a function of climate. Box (1981) developed a model that used six climate variables to predict 100 plant functional types. As stated earlier, Lookingbill and Urban (2005) stressed the need for more plant-relevant explanatory variables instead of their topographic proxies for forest site quality modeling. They compared two predictive models of forest species composition, one with

elevation as the predictor and the other using radiation, temperature, and soil moisture as the predictors. Results indicated that the latter had a success ratio of 73% versus 18% for the elevation model. Swenson et al. (2005) were able to predict the SI at 100 years for Douglas-fir [*Pseudotsuga menziesii* (Mirb.) Franco] as a function of monthly averaged climatic data and soil fertility (R^2= 0.55). Ohmann and Gregory (2002) reported that in coastal Oregon, species distributions were strongly related to regional climate and geographic location. In another study, Ohmann and Spies (1998) concluded that woody species composition was mostly a function of climate, but also explained by geology, disturbance, and topography. Monserud et al. (2006) predicted the SI at 100 years of lodgepole pine (*P. contorta* Douglas ex Louden var *latifolia* Engelm. ex S. Watson*)* as a function of July mean temperature, growing degree days, and the Julian date when growing degree days reaches 100.

Using digital terrain data to derive variables for site quality modeling

Digital topographic data can be used to model many of the environmental characteristics of a forested site to determine site quality. Elevation, aspect, slope gradient, curvature, and flow accumulation are some of the more basic elements that can be derived from a digital elevation model (DEM) for use in site quality modeling. Specific (or upslope) catchment area has been found to correlate with variations in soil moisture and runoff volume (Davis and Goetz, 1990; Moore et al., 1988). Slope curvature is related to soil water content, as described by the TSI (McNab, 1989). Bolstad et al. (2001) implemented the TSI in a GIS and used it to describe species distribution in North Carolina. Iverson et al., (1997) created the IMI, a GIS-derived index of hardwood site quality based on hillshade, curvature, total soil water holding capacity, and flow accumulation. The FSQI (Meiners et al., 1984) originally devised as a field method based on aspect, slope position, and slope gradient, can be easily modeled from a DEM. Flanigan et al. (2008) were able to predict the abundance of five hardwood tree species in West Virginia based on aspect, curvature, and slope change derived from a DEM. Jensen and Domingue (1988) contributed to the literature by developing a commonly used flow accumulation model for use within a GIS.

Boerner (2006), in his review of site quality properties of the southern Appalachians, stated that GIS technologies now allow scientists to go from local plot-based studies to broad-

scale predictions over regional areas, which has been previously impossible. In the southern Appalachians, where many environmental gradients and disturbance patterns are often correlated with topography, the use and analysis of digital terrain data allows the prediction of ecological types and variables with much higher efficiency (Odom and McNab, 2000). Host et al. (1996) integrated climatic and physiographic GIS-derived grids to identify regional landscape systems in northern Wisconsin. Other notable and robust multivariate models that have been developed in conjunction with GIS-derived variables include Odom's (1998) study that addressed forest classification in North Carolina, and Abella's (1993) investigation that modeled the abundance and distribution of eastern hemlock in the mountainous regions of South Carolina and North Carolina. By creating layers of information through GIS, managers can now derive, observe, and analyze combinations of site quality variables in ways that were previously impossible on a spatial and temporal basis.

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Chapter 2

Predicting Upland Hardwood Site Quality in the Southern Appalachians using FIA Data and Geospatial Modeling

1. Introduction

Evaluation of site quality in mountainous terrain is a challenge. The upland hardwood forest ecosystems of the southern Appalachians are some of the most complex and diverse in North America due to the combination of topography, geology, climate, and soil found throughout the region. These attributes lead to a wide range in site quality and productive capacity across the region, driven largely by climatic and topographic controls on water availability (Smith, 1994). Disturbance is also a factor, since most of the hardwood forests of the region have been harvested multiple times, often leaving the forest in a degraded condition (Deluca et al., 2009).

Site quality is a measure of the potential productivity of an area. Site can be expressed indirectly through the local climate, topography, soils, and vegetation present, and directly by growth of trees (Helms, 1998; Johnson et al., 2002). Site quality is most commonly estimated using site index (SI), based on the total height of a tree at a designated age, which is typically 50 years for eastern hardwood species. Unfortunately, SI may not accurately measure site quality in the southern Appalachians. Using SI, the selected trees must have been in a dominant or codominant crown class their entire life, have no damage to the apical meristem, and be free from damaging agents that affect growth. Because of the disturbance history in hardwood forests of the southern Appalachians, these assumptions are seldom met. The validity of SI as a measure of site quality also relies on the assumption that height growth is independent of stand density. Recent research has demonstrated that this assumption may not be valid (MacFarlane et al., 2000). Due to these issues, management tools are needed that are based on the characteristics of the site to quantify the site quality.

Landform is related to site quality, species composition, and forest productivity in the southern Appalachians. Early studies by Braun (1950), Whittaker (1956), Carmean (1975), and

Smalley (1984, 1986) all served to establish well-known relationships between the distribution of forest tree species and their environment. Hack and Goodlett (1960) originally suggested that landform modified the way water moved across the forested landscape, which in turn was related to the distribution of forest vegetation in the southern Appalachians. It was this premise that inspired the creation of the Terrain Shape Index (TSI) (McNab, 1989). The TSI provides a measure of the concavity or convexity of the landform. Defined as the mean relative difference in elevation between the center of a plot and its boundary, the TSI generates positive values to indicate convex or water-shedding landforms (ridges, spur ridges, nose slopes), and negative values to indicate concave or water-holding landforms (creek beds, coves, bottoms). The original development of the model related the TSI to yellow-poplar (*Liriodendron tulipifera* L.*)* site index in the Blue Ridge. Meiners et al. (1984) examined the effect of topography on available water in the Ridge and Valley of southwestern Virginia to create the Forest Site Quality Index (FSQI). The FSQI combined field measures of slope position, slope percent, and aspect to predict site quality. The underlying premise was the same as the TSI: certain landforms have more available water for plant growth than others.

Soil characteristics, especially depth and texture, have also been found to correlate with site quality. Baker and Broadfoot (1979) devised a field classification for several commercially important southern hardwoods based on the physical, moisture, nutrient, and aeration properties of the soil to assess the potential productivity of a site. Jones (1987) stated that it was too difficult to distinguish between the very best and other levels of site quality based on stand and tree measures alone. As a result, Jones and Saviello (1991) developed a way to determine site quality for hardwood growth based on slope position and soil characteristics, such as texture, stoniness, and depth. More recently, Iverson (1997) developed a GIS-driven integrated moisture index (IMI), based on flow accumulation, curvature, hillshade, and the total water holding capacity of the soil, that explained 64% of the variation found in upland oak SI within stands on the Allegheny Plateau. However, one of the issues of using soil characteristics to determine site quality is scale. Detailed, or second order soil surveys, at a scale of 1:12000 – 1:32000, can provide the information on site quality needed for site-specific management (Brady and Weil, 2002). The soils in much of the southern Appalachians have been mapped and, in theory, should provide reliable estimates of site quality. Unfortunately, existing soil maps were frequently

compiled using third order surveys with frequent mapping of complexes and associations rather than specific series. This approach has resulted in maps with too coarse a spatial resolution to be useful for site-specific forest management.

Where accurate measures of SI do not exist in the southern Appalachians, vegetation has been used to infer the quality of the site. Groups of tree species are known to occur together across the forested landscape due to similar site requirements (Eyre, 1980; Smith, 1994). Whittaker (1956) was one of the first to quantify the relationships between the distribution of upland hardwood tree species and their environment in the Southern Appalachians. He found that tree species respond to gradients of temperature and moisture, and from this observation, four classes of soil moisture were determined to exist in the mountains: mesic, submesic, subxeric, and xeric (Whittaker, 1966). Each of these soil moisture classes was assigned an index weight, with the higher index numbers indicating greater moisture. Within plots across the Great Smoky Mountains, commonly occurring hardwood and conifer species were evaluated to determine their site requirements, particularly those related to moisture and elevation. From these observations, each species was assigned to a moisture class based on where it occurred most frequently. Whittaker used the weighted average of all trees' index values within each plot to determine the site quality. He found the index to be highly correlated to forest productivity across a wide environmental gradient in the Great Smoky Mountains (Whittaker, 1966). A similar approach, the Moisture Regime Index (MRI), based on the presence or absence of a species, explained 62% of the variation in yellow-poplar SI in the Blue Ridge Mountains of western North Carolina (McNab and Loftis, in press).

A good opportunity to study site quality exists in the extensive database of forested conditions that are recorded by the USFS Forest Inventory and Analysis (FIA) Program. The FIA program is designed to provide data on the extent and properties of the forests in the United States (USDA, 2010). The FIA database is the only continuous national- and regional-scale database of current and historical forest conditions in the nation, which is why it was chosen for this study.

Because detailed information is not widely available to correctly predict site quality in this region, the overall objective for this study was to determine if site quality could be accurately determined based on topography, species composition, and soil attributes. Specifically, three hypotheses were tested: 1.) FIA measures of forest productivity are related to one another; 2.) FIA measures of forest productivity are related to FIA-measured and GIS-derived landscape parameters; and 3.) FIA measures of forest productivity are related to independent measures of forest productivity, which are based on landscape parameters and soil characteristics.

2. Methods

2.1 Study area

The study was conducted in the upland hardwood forests within six counties located entirely within the mountainous Blue Ridge of western North Carolina (Fig. 2.1). Bailey (1995) described the area as being part of the Central Appalachian Broadleaf Forest Province. The Natural Resource Conservation Service has designated the area as the Southern Section of the Blue Ridge Province of the Appalachian Highlands (USDA, 2006). The terrain is heavily dissected and the parent material is composed of mostly crystalline and some sedimentary rocks. Primary soil orders include Inceptisols and Ultisols with an udic moisture regime (USDA, 2006). Elevations within the study area range from 205 to 2036 m above sea level. Climate is temperate, with mean annual temperature ranging from 10 to 17 ^{O}C. Average annual precipitation ranges from 900 to over 2000 mm, the highest in the eastern U.S. The six counties cover approximately 780,000 ha, or 34% of the Blue Ridge within North Carolina.

Five distinct forest types prevail that are primarily controlled by a moisture gradient that varies with elevation and aspect. As a general rule, as elevation increases, one would sequentially encounter oak-pine forests, Appalachian oak forests, northern hardwood forests, and at the highest elevations, spruce-fir forests (Bailey, 1995). Aspect is an important determinant of forest communities as well, so that site-demanding species will often be found at higher elevations on north to northeast aspects and at lower elevations on south to southwest aspects. Remnants of mixed mesophytic forests may be found in the protected coves of the mountains where the soil and water accumulate.

2.2 General approach to data collection

Plots were extracted from the FIA database, along with selected landscape, site quality, location, and tree data from the plots. For each plot the soil mapping unit was identified within the Soil Survey and Geographic (SSURGO) database, and from this the available water supply was extracted (Soil Survey Staff, NRCS, USDA, 2009). Additional landscape attributes and site quality indices were extracted from a 10 m digital elevation model (DEM). A master list of variables, their description, source, and how they were used in the study may be found in Table 2.1.

2.3 Variables from the FIA database

FIA data is used to direct forest policy and programs, as well as to drive numerous ecological analyses across the nation. To accurately capture the condition of the forests within these plots, multiple attributes are measured at three different scales, represented by Phases (USDA, 2010). Phase II is ground-sampled data measured within multiple permanent fixed-radius plots that are each designed to cover 0.41-ha (1-ac) (Fig. 2.2). Overstory tree and stand attributes are the parameters measured at this level. Phase II data collected from the inventory year 2002, or Cycle 7, was used for this analysis (USDA, 2010).

Inventory foresters annually measure a portion of the Phase II plots (hereafter referred to as "FIA plots"). This data is then organized and entered into several tables within the overall database. The PLOT, COND, TREE, and SITETREE tables contained the information used to conduct this study (USDA, 2010). Data extracted included the location information for the plots, such as the state, county, measurement year, month, and date, as well as the actual geographic coordinates. The species, condition (live, dead, or removed), damage, and tree class code (growing stock, rough cull, rotten cull) were collected for all trees within the plots. Ownership, forest type, condition status (forest, non-forest, water), slope percent, aspect, evidence and type of disturbance, physiographic class, SI, site productivity, and silvicultural treatment were also extracted for each plot. The SI was estimated from the measured heights of site trees at base age 50. Site productivity is an ordinal value that is assigned to the plot that classifies the site based on its inherent capacity to grow crops of industrial wood; it is based on the site trees found in a plot (USDA, 2010). Physiographic class is a nominal code assigned to all plots that considers the

general effect of landform, topographic position, and soil on moisture available to trees (USDA, 2010). Site index varies with species, so it was necessary to have the species and age for which the recorded SI value was based (USDA, 2010).

2.4 Standardization of the FIA SI values

The SI values within the FIA database were standardized to three separate sets of SI estimates: white oak (*Quercus alba* L.*)*, yellow-poplar, and upland oak. White oak was chosen because it is ubiquitous throughout the southern Appalachians and it can occur on a wide range of soils (Rogers, 1990). Yellow-poplar is a site demanding species and occurs on deep, well drained soils on good sites (Beck, 1990); it is also related to the TSI. Upland oak was used because it is related to the FSQI and the IMI. Conversion equations were from Doolittle (1958), Olson and Della-Bianca (1959), and Johnson et al. (2005).

2.5 Screening of the FIA database

Screening of the FIA database was done to ensure that the FIA plots used in this analysis were forested and minimally disturbed. The original FIA database for Cycle 7 in North Carolina contained 5908 plots. Of these, 930 occurred in the Blue Ridge physiographic province. Seven hundred and sixty-seven plots were on were forested land. The actual locations of the FIA plots were required in order to accurately relate the environmental characteristics of the site to the point estimates of productivity, so any plots that did not have a recorded location were removed. Plots with a recorded disturbance code or silvicultural treatment code of any type were excluded to ensure the results were not a reflection of disturbance or management. Disturbances were recorded on plots if they covered at least one acre, occurred since last measurement, and caused damage or mortality to 25% of the trees within the plot (USDA, 2005). Further screening provided that the plots be within the six study counties. SSURGO data, which were used in this study to determine available water supply of the soil series in the study area, were not available for Swain County, NC (Soil Survey Staff, 2009). This led to the exclusion of 15 plots that were in that county. It was discovered that some of the FIA plots had duplicate geographic coordinates for the actual plot locations; these were removed from the dataset. A final analysis of the tree species within the plots indicated there were high-elevation spruce-fir communities

within the database. These were taken out as well. The final number of plots analyzed for this study was 203 (Appendix A).

2.6 Available water supply from the SSURGO database

Whole-profile available water supply was derived for each FIA plot from the mapping unit data in the spatial and tabular databases from the SSURGO database. SSURGO data were obtained for Buncombe, Haywood, Jackson, Madison, and Yancey Counties, NC, as well as the Smoky Mountains (Soil Survey Staff, 2009). Spatial data for Swain County were not available. Available water supply is the total volume of water available to plants at field capacity, or the water that a soil can hold against the force of gravity (Brooks et al., 2003), for the full depth of the soil described. It is a weighted value based on the components within the mapping unit.

2.7 GIS extractions and independent measures of site quality

A 10 m DEM was obtained from the U.S. Geologic Survey National Elevation Dataset (Gesch et al., 2002; Gesch, 2007). Basic surface analyses, including aspect and slope percent were generated from the DEM using ArcGIS 9.3 (Hillier, 2007). Elevation was extracted from the DEM for all plots.

Hydrological characteristics of the area were used to calculate a measure of slope position (summit, shoulder, backslope, toeslope, footslope, and floodplain) from the DEM. Two grids were developed that depicted downhill and uphill flow length between ridges and streams. The two flow length grids were then used in the following algorithm:

$$\textit{Slope Position} = \textit{Downhill flow length}/(\textit{Uphill flow length} + \textit{Downhill flow length}) \qquad (1)$$

where *Slope Position* is expressed as a percent, *Downhill flow length* is calculated as the longest flow path, in meters, from each cell to a sink or outlet on the edge of a raster, and *Uphill flow length* is calculated as the longest upslope distance, in meters, along the flow path from each cell to the top of the drainage divide (Hillier, 2007). This calculation allowed for an index of slope position as a percent of the slope distance, where 0% slope position represented the bottom of the slope at stream edge and 100% was at the local ridge top. The final slope position was classified

into six classes using quantiles to guide the breaks. By comparing this final grid to the original DEM along with a digital raster graphic of the topographic map, positions on the final grid were classified into the six aforementioned slope positions.

Four independent measures of site quality were generated to compare to the FIA measures of site quality. They were chosen because they are largely based on water availability, which is regarded as the most limiting factor to tree growth in the southern Appalachians (Smith, 1994). Included were the MRI (McNab and Loftis, in press), the FSQI (Meiners et al., 1984), the IMI (Iverson et al., 1997), and the TSI (McNab, 1987). Three of these were modeled in a geographic information system (GIS), (the FSQI, the IMI, and the TSI) and values were extracted for the FIA plot locations.

In order to calculate the MRI, a tree list was created for each FIA plot and the MRI value was assigned to each tree species present within the plot (see Appendix C). These values were then averaged on a plot-level basis in the original equation (McNab and Loftis, in press).

$$MRI = (\Sigma\, a) / n \qquad (2)$$

where *MRI* is the plot-level Moisture Regime Index, $\Sigma\, a$ is defined as the sum of the MRI values for all species present within the plot, and n is the number of individual species within the plot. A modification was made to the original model to refine the index value for red maple (*Acer rubrum* L.*)*. Instead of using the original index value of 0, a value of 2.5 was assigned to this species. Although red maple does occur in a wide range of sites, it is most commonly seen in a subxeric environment in the study area, which would reflect a value 2.5. The MRI values were classified as xeric (1.0-1.9), subxeric (2.0-2.5), submesic (2.6-3.0), and mesic (3.1-4.0).

The FSQI was calculated in a GIS by reclassifying the aspect, slope position, and slope (%) grids to reflect the ordinal values (scores) originally assigned by the authors (Table 2.2) (Meiners et al., 1984). The reclassified grids were added to produce a final FSQI grid, which had a value range of 3 to 16. FSQI values were then used to predict upland oak SI values for all plots in this study (Table 2.3) (Meiners et al., 1982).

$$FSQI = AS + SLP + SLPS \quad (3)$$

where *FSQI* is the plot-level Forest Site Quality Index, *AS* is the FSQI score of the measured aspect (degrees), *SLP* is the FSQI score of the measured slope (percent), and *SLPS* is the FSQI score of the GIS-derived slope position (percent).

The IMI combined weighted estimates of topographic and soil parameters to produce an index of site quality (Iverson et al., 1997). In our study, hillslope, curvature, and flow accumulation grids were derived from a 10 m DEM. Whole-profile available water supply (mm) was derived from SSURGO data (Soil Survey Staff, NRCS, USDA, 2008). The four parameters were standardized on a 0-100 scale, weighted by the coefficients below, and combined to produce a final grid of the IMI. The final index values may range from 0-100 with high index numbers indicating high site quality.

$$IMI = 0.40\ (hillshade) + 0.30\ (flow\ accumulation) + 0.10\ (curvature) + 0.20\ (available\ water\ supply) \quad (4)$$

where *IMI* is the plot-level Integrated Moisture Index, *hillshade* is a grid produced from the 10 m DEM to represent the amount of insolation received from the sun and protection given from adjacent landforms, *curvature* is a grid produced from the 10 m DEM to represent the curvature of the land, and *available water supply* is an estimate of plant available water. The IMI values were then converted to upland oak SI values based on the following linear equation. Iverson et al. (1997) accounted for 64% of the variation between actual upland oak SI and predicted upland oak SI using the IMI and this same equation:

$$Upland\ Oak\ SI_{50}\ (m) = 0.1219\ (IMI) + 15.088 \quad (5)$$

No standard GIS algorithm has been developed to represent the TSI in a GIS. For this application it was determined, after working with several iterations, that the following algorithm best captured the TSI within the study area:

$$TSI = (P - A) / R \quad (6)$$

assuming a circular plot with a radius of 75 m, where *TSI* is the Terrain Shape Index, *P* is the elevation of the subject grid cell, *A* is the average elevation of grid cells at a radius *R* from the subject grid cell, and *R* is the radius in distance units, which was 75 m for this purpose. Depending on where the TSI is applied, the range of final values can vary, but they are always distributed around the value 0, which represents a planar slope. The TSI values for each plot were converted to yellow-poplar SI values using the original linear equation from McNab (1989), who was able to explain 51% of the variation between actual yellow-poplar SI and predicted yellow-poplar SI using the TSI:

$$\textit{Yellow-poplar } SI_{50} \textit{ (m)} = 53.6\ (TSI) + 32.9 \quad (7)$$

2.8 Statistical analysis

Spearman's rank correlation coefficient (ρ) and a *p*-value were calculated for all pair-wise relationships of the variables to determine the strength and significance. Spearman's correlation coefficient is calculated the same as Pearson's correlation coefficient, but where Pearson's uses the actual values of the data to calculate the coefficient, Spearman's uses the ranks of the observations. The main advantages of Spearman's are that it is not as sensitive to outliers and it does not require a linear relationship between the response and the predictor. For this reason it is often referred to as nonparametric. When generating a scatter plot of Spearman's correlation coefficients, the literal ranks of the data are plotted versus the actual data values. So for example, a data point that is the second-largest X value and the fourth-largest Y value would be plotted as (2, 4). SAS/STAT® Software Version 9.2 was used for all statistical analyses.

3. Results

3.1 Condition within the plots

Measured parameters in the 203 FIA plots in this study varied considerably (Table 2.4). Within the study area there were 69 species of hardwood and softwood trees recorded in the FIA database. White Oak SI values ranged from 12 m to 33 m (39 to 108 feet), indicating a wide range in site quality. The range of yellow-poplar SI values was slightly larger, 6 m to 45 m (20

to 148 feet). Upland oak information is not presented in the results because the values matched the values of white oak. The range of FSQI values (3 to 14) also indicated a wide range in site quality across the plots. A wide range of aspects was recorded. On average, plots were located in areas with steep slopes and on high slope positions.

3.2 Correlations between FIA measures of forest productivity

The results of all pair-wise comparisons between the study variables may be found in Table 2.5. Results will either refer to that table or they will be presented in a separate correlation matrix to emphasize particular relationships. To keep things in perspective, only significant correlation coefficients that are equal to or greater than +/- 0.20 will be discussed.

Correlation analysis performed on FIA measures of forest productivity (WO SI, YP SI, standing basal area, standing volume, and site productivity) revealed that all pair-wise relationships were significant to some degree (Table 2.6). The relationship between YP SI to WO SI had a high correlation coefficient (ρ = 0.72), but this was due to both measures being based on the same tree prior to conversion. The correlations between FIA site productivity to WO SI and YP SI were the highest among the FIA measures of productivity (ρ = -0.58 and -0.77, respectively). The ordination of the FIA site productivity codes assigns the lowest number to the highest potential productivity; thus, the inverse relationship to SI. FIA standing basal area and FIA standing volume had the lowest correlations to the other measures, but they were correlated to each other, which would be expected since they are both diameter-based.

3.3 Correlations between landscape parameters and FIA measures of forest productivity

The FIA measured landscape variables were poorly correlated to FIA standing volume and FIA standing basal area in the study (Table 2.5). GIS-derived elevation was significantly correlated to FIA site productivity (ρ = 0.28). GIS-derived slope position was significantly and negatively correlated to YP SI (ρ = -0.22) and GIS derived-elevation was negatively correlated to WO SI (ρ = -0.25). FIA physiographic class could not be included in the correlation analysis since it was nominal, but it was charted for frequency to see if any patterns emerged (Fig. 2.3). Most of the plots were designated as moist slopes and coves, with a smaller number being classified as small drains.

3.4 Correlations between independent measures of forest productivity and FIA measures of forest productivity

The independent measures of forest productivity were correlated to WO SI, and the MRI and the FSQI were the highest and most significant (ρ = 0.21 and 0.27, respectively, $p < 0.0001$ for both) (Figs. 2.4 and 2.5, Table 2.7). These two independent measures of forest productivity were also correlated to YP SI (Figs. 2.6 and 2.7, Table 2.7). The highest correlation seen in Table 2.7 was between the MRI and YP SI (ρ = 0.38). The MRI was the only independent measure of forest productivity significantly correlated to FIA standing basal area, and none of the independent measures of forest productivity correlated significantly to FIA standing volume. All of the independent measures of forest productivity were significantly correlated to FIA site productivity, and the MRI (ρ = -0.23), the FSQI (ρ = -0.29), and the TSI (ρ = 0.20) all had coefficients equal to or over 0.20.

4. Discussion

4.1 Correlations among FIA measures of forest productivity

This analysis revealed that the independent measures of forest productivity had some of the highest and most significant correlations to the FIA measures of SI. The correlations to the independent measures of forest productivity were very similar among the FIA measures of WO SI, YP SI, and FIA site productivity (Table 2.7). These results suggest that if FIA measures of SI could not be obtained, it appears that FIA site productivity could be an acceptable substitute. As stated earlier, the FIA site productivity code is based on the site trees within a plot. Yellow-poplar is known to be a very site demanding species, and the relatively high correlation coefficient between YP SI and FIA site productivity (ρ =-0.77) reflected this species' preference for the very best sites. Similarly, the lower correlation between WO SI and FIA site productivity (ρ = -0.58) indicated that slower growing more tenacious white oaks do not indicate high site quality. These results support the case of using indicator species for determining site quality. Given this relationship, it was surprising that the MRI, which is also based on the site preferences of tree species, specifically the moisture regime preferences, did not correlate higher to FIA site productivity. The MRI is based on all trees present in a plot, where FIA site productivity is based on site trees, which are typically the best trees around. This could have been a reason why the correlation was not higher.

4.2 Correlations between landscape parameters and FIA measures of forest productivity

The three FIA-measured landscape parameters included in this study, aspect, slope percent, and physiographic class, did not correlate or reveal any patterns indicating site quality or forest productivity. This begs the question: decades of site quality research and forest site classification in this region have suggested otherwise. Muller (1982) found a strong correlation between aspect and the distribution of shagbark hickory [*Carya ovalis* (Wangenh.) Sarg.], bitternut hickory [*C. cordiformis* (Wangenh.) K. Koch], and mockernut hickory [*C. tomentosa* (L.) Nutt.]. Significant differences in growth were found in yellow-poplar, chestnut oak (*Q. prinus* L.), and red maple growing on northeast versus southwest slopes (Fekedulegn et al., 2003). Further, Fekedulegn et al. (2004) found that north and east aspects were 27-50% more productive than west and southwest aspects with regard to hardwood volume. The differences in that study were driven by differences in microclimate between the cooler and warmer aspects, particularly temperature and humidity. McNab (1991) found elevation, aspect, slope gradient, and indexes of landform to account for 97% of the variation in forest types in Bent Creek Experimental Forest, which is within the study area. It could be that the error introduced into FIA landscape data through field measure renders it not useful for applications such as this. However, FIA maintains that both field-measured slope and aspect must be within +/- 10% of their true values at least 90% of the time it is measured (USDA, 2007). Another possibility is that the FIA landscape data may not be precise enough for this level of investigation. For example, the FIA Database Description and Users Guide lists and describes sixteen different physiographic class codes, of which nine could potentially be found within the study area (USDA, 2010). However, for the 203 plots in this study, only four physiographic class codes were assigned, and of those four, one class contained 65% of the plots (Fig. 2.3).

4.3 Correlations between independent measures of forest productivity and FIA measures of forest productivity

As hypothesized, independent measures of forest productivity did significantly correlate to FIA measures of forest productivity within the plots. The MRI, the FSQI, the TSI, and the IMI were significantly correlated to YP SI. Additionally, the same held true for all four indices and WO SI, and the highest coefficients were to the MRI and the FSQI. Indicator species are known to related to site quality in the study area. For instance, McNab et al. (2002) found

yellow-poplar and white ash (*Fraxinus americana* L.) to be significantly correlated to sites of high productivity, and scarlet oak (*Q. coccinea* Muenchh.*)* and chestnut oak to be to indicators of low site productivity. Another study found that tree species could be used to define ecoregions upon the Cumberland Plateau in Tennessee (McNab et al., 2004). This suggests that the composition of tree communities can be powerful in delineating areas that have similar site characteristics. The correlation coefficient between the MRI and YP SI was almost twice that found between the MRI and WO SI correlation, which provides more support of yellow-poplar as an indicator species. Yellow-poplar will compete successfully where there is abundant moisture. As water is one of the most limiting resources to tree growth in the region, these results suggest that the MRI can be used as a way to delineate site quality where there are no accurate estimates of site quality to be had.

The FSQI correlations to WO SI and YP SI, while significant, did not exhibit a great difference in their coefficients, as was seen in the MRI. The combination of slope position, aspect, and slope percent essentially will determine the path and storage of water that comes into the system. In this respect, it gives land managers an idea as to where specific species may compete successfully. The same can be said for the TSI, as it indicates where water will and will not be available for tree growth. Our observations indicated a similar relationship between the TSI and YP SI as what was reported by McNab (1987). Carmean (1979) stated that topographic features often correlated with hardwood SI include aspect, slope position, slope steepness, and slope shape. The correlations of the FSQI and the TSI may have been higher had a measure of climate, particularly precipitation, been included. The annual precipitation within the study area varied tremendously, which may have had a greater effect on forest site quality than what could be captured by topography alone. Or, it may be that topography and terrain shape simply have a longer temporal effect on the vegetation and quality of a site. For example, Elliott et al., (1999) found that species associated with convex, or water-shedding, terrain, such as pitch pine (*Pinus rigida* Mill.*),* scarlet oak, and black oak (*Q. velutina* Lam.*)*, decreased in abundance over a 20 year period. Conversely, species associated with moister landscapes, such as yellow-poplar, Eastern hemlock [*Tsuga canadensis* (L.) Carriere]*,* and rhododendron (*Rhododendron maximum* L.*)* increased in abundance over the same period. The results of the current study show that

topography can be used to delineate site quality within the study area, but it may only account for part of what is going on in these forested sites.

Initially, the IMI was considered to be a good candidate for predicting forest productivity because it incorporated a measure of available water supply, driven by soil texture and depth. The original study area for Iverson's work was relatively small (19 ha), and did not have a lot of variation in topography, geology, soils, climate, or vegetation (Iverson et al., 1997). Resolution and scale of the available soils data may have been the key issue that contributed to the lack of correlation between the IMI to WO SI and YP SI. In the original study, Iverson et al. (1997) used a soil map that had a scale of 1:15,840, and in this study our soils were mapped at 1:25,000. This is a significant and common issue in using soils data to predict site quality (Swensen et al., 2005). It is clear from the literature that soil depth and texture are primary influences on forest site quality, but accurately capturing those characteristics, particularly across large landscapes, has proven to be an issue (Gessler et al., 1995).

In the Appalachians, soils have been mapped very coarsely, and the use of complexes, associations, and undifferentiated groups are often represented by a single name. Second-order surveys, with a scale of 1:12,000 to 1:32,000, are the level of resolution required for forest management. Where there has been data with sufficient detail, soils have been used successfully to predict site quality (Baker and Broadfoot, 1977; Jones and Saviello, 1991; Fralish, 1994; Iverson et al., 1997; Yeakley et al., 1998). Further work will be needed to determine if the IMI can be used to accurately predict site quality in the southern Appalachians. Because of the effort required to accurately map soils across broad landscapes, soil storage may prove to be one of the more challenging aspects to accurately predicting site quality.

5. Conclusion

In the Blue Ridge Mountains of North Carolina, vegetation is a function of site quality, and forest productivity and site quality are a function of topography. FIA measures of forest productivity were not correlated to FIA measured landscape parameters, despite the numerous relationships that have been established in the literature. FIA site productivity classes were significantly correlated to FIA measures of SI. As FIA site productivity is based on site trees,

the case for indicator species can be made for identifying site quality in the study area. This was also reflected in other results of the study. Independent measures of forest productivity, particularly the MRI and the FSQI, were found to be significantly correlated to FIA measures of SI. These results, taken as a whole, suggest that where accurate measures of site quality do not exist or cannot be measured directly, there may be two alternatives. If a tree inventory is available the MRI can predict site quality based on species composition. A second, and perhaps more efficient approach may be to delineate site quality by modeling the FSQI with a 10 m DEM, which is from a database available for public use. This latter method could give a land manager a first approximation about where to focus his efforts, and additional layers of information, such as precipitation or soil storage, may improve the predictions. The GIS approach within this analysis provides the ability to map all forests into SI classes for management planning.

This study allowed for a unique opportunity to work with the actual locations of FIA plots and the extensive database on the forested conditions found therein. There is tremendous potential to this type of site quality modeling in the complex terrain of the southern Appalachians. The results of this study have shown that FIA measures of productivity, particularly SI and site productivity, can be used as the measured variable in the predictive modeling of site quality. This alone is a key value to the literature in this field. FIA data can be used in this type of investigation, which may eventually serve to increase the efficiency with which we manage our forests.

6. Acknowledgements

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Table 2.1. All variables, their description, source, and how they were used in the study.

Variable	Description	Source	How it was used in the study
FIA Plot Variables:			
FIA SI	Original measured site index, base age 50, from the FIA plot, based on various site trees; reported in meters	FIA database	Standardized to separate WO SI and YP SI values for all plots
Location	State, county, and plot in which the FIA plot was located	FIA database	Used to determine inclusion in the study
Measurement date	Day, month, and year when the FIA plot was measured	FIA database	Used to determine inclusion in the study
Actual geographic coordinates	The actual location of the plot (lat/long) in the Geographic Coordinate System North American Datum 1983	FIA database	Used to extract GIS-derived variables for the plots
Tree species	The species of each tree measured within the FIA plot	FIA database	Used to determine inclusion in the study (in the case of spruce-fir plots); used to calculate MRI
Tree condition	Described the condition of individual trees measured in the FIA plot; live, dead, or removed	FIA database	Used to determine inclusion in the study
Damage	Described the type and extent of any damage that individual trees within the FIA plot since last measurement	FIA database	Used to describe the plots
Tree class code	Described the individual trees measured in the FIA plot as growing stock, rough cull, or rotten cull	FIA database	Used to describe the plots
Ownership	Described the FIA plot as being on public or private land	FIA database	Used to describe the plots
Forest type	Described the tree species assemblage within the FIA plot	FIA database	Used to describe the plots
Plot condition	Described the FIA plot as being in forest, non-forest, water	FIA database	Used to determine inclusion in the study
Slope	The slope of the FIA plot; reported in percent	FIA database	Used to describe the plots
Aspect	The aspect of the FIA plot; reported as azimuth in degrees	FIA database	Used to describe the plots
Disturbance	Described the type and extent of any disturbance the FIA plot had incurred since the last measurement	FIA database	Used to determine inclusion in the study

Variable (cont.)	**Description** (cont.)	**Source** (cont.)	**How it was used in the study** (cont.)
FIA Plot Variables:			
Silvicultural treatment	Described the type of silvicultural treatment the FIA plot had incurred since the last measurement	FIA database	Used to determine inclusion in the study
Site Tree	Tree spp. upon which the SI measurement had been based	FIA database	Used to standardize the FIA SI values into WO SI and YP SI
Standing Basal Area	Live tree basal area for all trees > 2.54 cm diameter at breast height within the plot; reported in m^2 ha^{-1}	FIA database	Used as an estimate of productivity
Standing Volume	Net cubic foot volume in the saw-log portion for all trees in the plot > 28 cm at diameter at breast height; reported in m^3 per plot	FIA database	Used as an estimate of productivity
Site Productivity	An ordinal code that describes the plot in terms of inherent capacity to grow crops of industrial wood	FIA database	Used as an estimate of productivity
Physiographic Class	A nominal code that describes the effects of topography, landform, and soil on moisture available to trees	FIA database	Used to describe the plots
Standardized FIA SI Variables:			
White oak SI	Converted FIA site index standardized to WO SI, base age 50; reported in meters	Converted from FIA SI	Used as an estimate of productivity
Yellow-poplar SI	Converted FIA site index standardized to YP SI, base age 50; reported in meters	Converted from FIA SI	Used as an estimate of productivity
SSURGO Data:			
Available water supply	The weighted average of the available water supply for the whole profile of a mapping unit; reported in millimeters	SSURGO	Used in the calculation of the IMI
GIS Extractions:			
Aspect	GIS derived landscape variable; the direction of a slope face; reported as azimuth in degrees	10 m DEM	Used in the calculation of the FSQI
Slope	GIS derived landscape variable; rise/run; reported in %	10 m DEM	Used in the calculation of the FSQI

Variable (cont.)	**Description** (cont.)	**Source** (cont.)	**How it was used in the study** (cont.)
GIS Extractions:			
Slope position	GIS derived landscape variable; position on the profile of a slope (ridge, shoulder, sideslope, footslope, toeslope, and bottom; reported as a percent	GIS algorithm calculated from a 10 m DEM	Used in the calculation of the FSQI
Elevation	GIS derived landscape variable; reported in meters	10 m DEM	Used to describe the plots
Hillshade	GIS derived	10 m DEM	Used in the calculation of the IMI
Flow accumulation	GIS derived landscape variable; depicts the flow of water in the watershed based on upslope contributing area and slope	10 m DEM	Used in the calculation of the IMI
Curvature	GIS derived landscape variable; describes the curve of the land	10 m DEM	Used in the calculation of the IMI
IMI	The Integrated Moisture Index (Iverson et al., 1997); index of productivity based on topography and soil moisture	GIS algorithm	Used as an independent estimate of productivity
FSQI	The Forest Site Quality Index (Meiners et al., 1984); index of productivity based on aspect, slope percent, and slope position	GIS algorithm	Used as an independent estimate of productivity
TSI	The Terrain Shape Index (McNab, 1989); index of productivity based on the shape of a landform within a plot	GIS algorithm	Used as an independent estimate of productivity
Other Variables:			
MRI	The Moisture Regime Index (McNab & Loftis, in press); index of productivity based on species presence/absence	Calculated from tree spp. in the FIA plots	Used as an independent estimate of productivity
Beers aspect	Transformation of aspect that weights moist aspects higher	Calculated	Used to describe the plots

Table 2.2. Ordinal values assigned to variables in the FSQI model (after Meiners et al., 1984).

FSQI Value	Aspect	% Slope	Slope Position
1	196-260	>=60	Shoulder
2	166-195; 261-280	45 – 59	Backslope
3	146-165; 281-340	30 – 44	Summit
4	0-20; 341-360	15 – 29	Footslope
5	81-145	0 – 14	Toe Terrace Floodplain
6	21-80		

Table 2.3. Predicted upland oak SI values that correspond to the FSQI index values (after Meiners et al., 1984).

FSQI Value	Upland Oak SI_{50} *(m)*	FSQI Value	Upland Oak SI_{50} *(m)*
3	14	10	21
4	15	11	22
5	16	12	23
6	17	13	24
7	18	14	25
8	19	15	26
9	20	16	27

Table 2.4. Descriptive statistics of the 203 FIA plots sampled for the study.

Variable	Mean	S.D.	Min	Max
WO Site Index (base age 50, m)	21	4	12	33
YP Site Index (base age 50, m)	25	7	6	45
Slope (%)	44	18	1	90
Aspect (degrees)	176	105	1	364
Elevation (m)	1002	250	510	1704
Slope Position (%)	94	13	7	100
Available water storage (mm)	159	56	0	280

Table 2.5. Spearman's correlation coefficients (ρ) and significance for relationships between all variables (n=203); *significant at α <=0.05; **significant at α <=0.0001; bold signifies significant correlations >=0.20 that are discussed in the study.

	WO SI	YP SI	Vol	BA	Site Prod	FIA Aspect	Beers Aspect	FIA slope	Slope Position	Elev	AWC	MRI	FSQI	IMI	TSI
WO SI	1.00														
YP SI	****0.72**	1.00													
Vol	*0.17	*0.22	1.00												
BA	*0.22	*0.24	****0.38**	1.00											
Site Prod	****-0.58**	****-0.77**	*-0.18	*-0.24	1.00										
Aspect	-0.03	-0.10	-0.03	0.02	0.05	1.00									
Beers	0.13	*0.17	0.12	0.07	*-0.15	**-0.60	1.00								
Slope	-0.08	-0.03	0.11	0.02	0.14	-0.00	0.05	1.00							
SlopePos	-0.10	***-0.22**	-0.05	-0.10	*0.20	0.04	-0.08	-0.12	1.00						
Elevation	***-0.25**	*-0.19	0.04	0.02	****0.28**	0.15	*-0.14	-0.09	**0.31	1.00					
AWC	0.09	*0.17	-0.10	0.02	-0.03	0.04	0.03	*-0.23	-0.05	0.11	1.00				
MRI	****0.21**	****0.38**	0.11	*0.14	***-0.23**	0.07	0.06	-0.01	*-0.16	*0.18	0.09	1.00			
FSQI	****0.27**	****0.29**	0.01	0.08	****-0.29**	**-0.38	**0.44	*-0.15	**-0.46	**-0.30	0.04	0.09	1.00		
IMI	*0.16	*0.16	-0.08	0.10	*-0.18	**-0.30	**0.60	-0.09	0.60	0.00	0.11	0.11	**0.45	1.00	
TSI	*-0.15	***-0.21**	-0.03	-0.07	*0.20	0.00	*-0.16	-0.09	**0.53	0.10	-0.13	*-0.20	**-0.29	0.02	1.00

Table 2.6. Spearman's correlation coefficient (ρ) and significance of relationship between FIA measures of forest productivity (n=203).

	WO SI	YP SI	Standing BA	Standing Vol.	Site Prod.
WO SI	1.00				
YP SI	**0.72	1.00			
Standing BA	*0.22	*0.24	1.00		
Standing Vol.	*0.17	*0.22	**0.38	1.00	
Site Prod.	**-0.58	**-0.77	*-0.24	*-0.18	1.00

** significant at $\alpha < 0.0001$
* significant at $\alpha < 0.05$

Table 2.7. Spearman's correlation coefficient (ρ) and significance of relationships between FIA measures of forest productivity and independent measures of forest productivity (n=203).

	FIA Measure of Forest Productivity				
	WO SI	**YP SI**	**Standing BA**	**Standing Vol.**	**Site Prod.**
MRI	**0.21	**0.38	*0.14	0.11	*-0.23
FSQI	**0.27	**0.29	0.08	0.01	**-0.29
TSI	*-0.15	*-0.21	-0.07	-0.03	*0.20
IMI	*0.16	*0.16	0.10	-0.08	*-0.18

** significant at $\alpha < 0.0001$
* significant at $\alpha < 0.05$

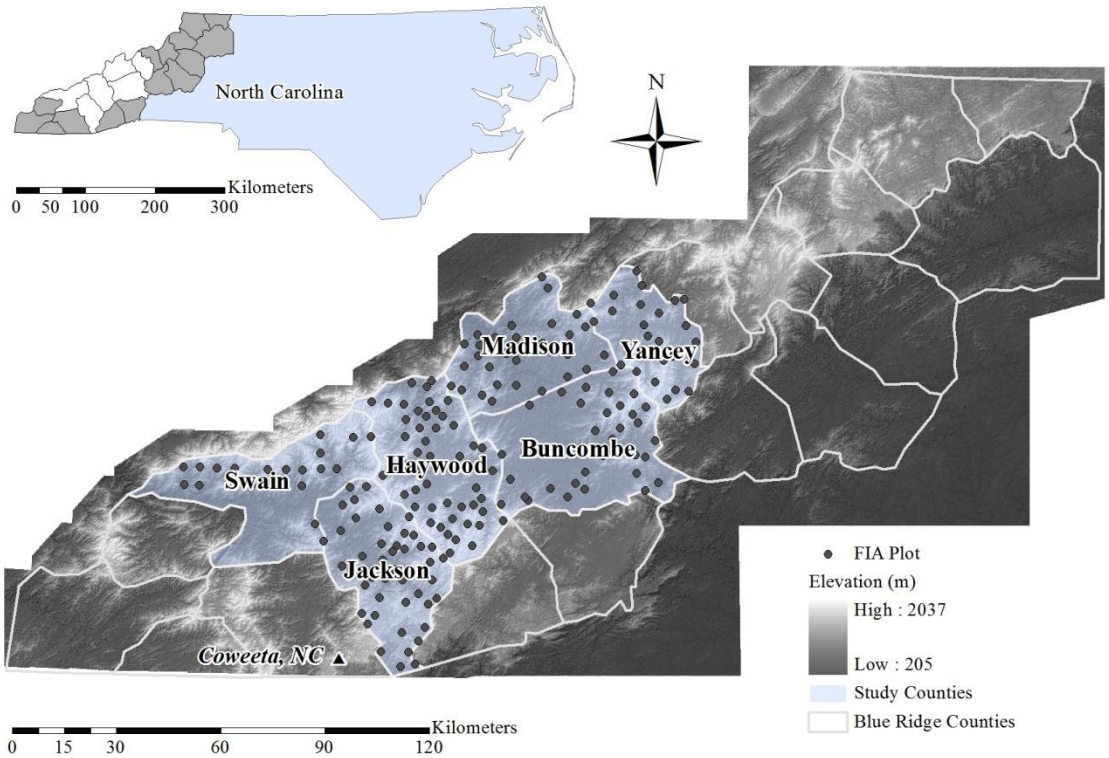

Fig. 2.1. Study area and approximate locations of the FIA plots (*n*=208) within the Blue Ridge Mountains of western North Carolina.

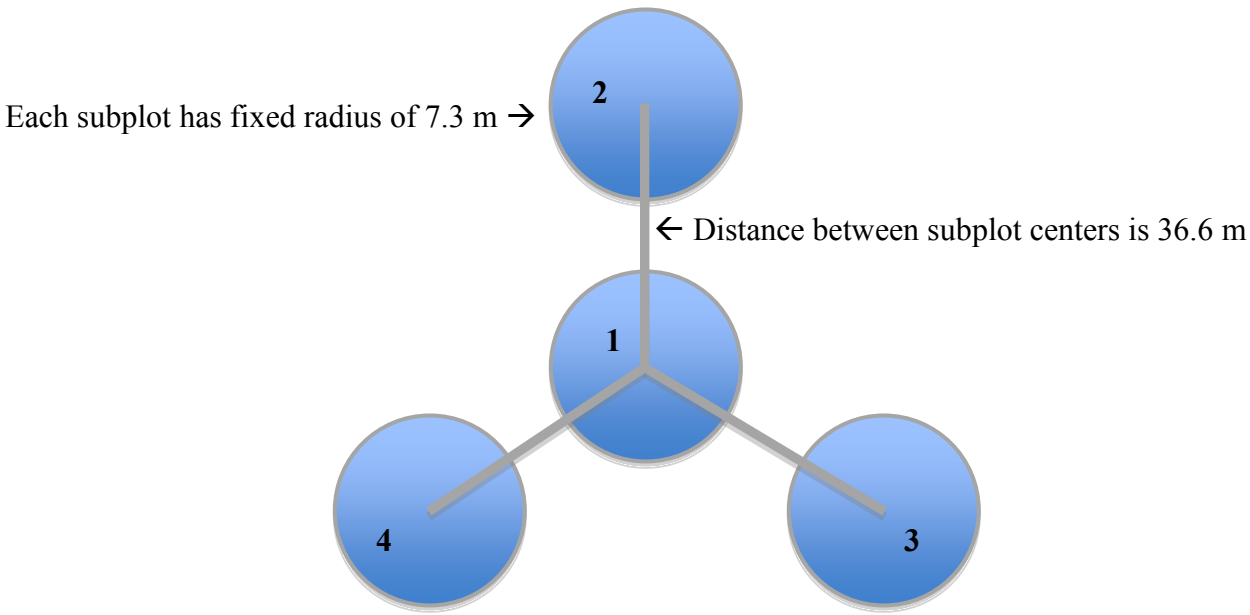

Fig. 2.2. Example of an FIA mapped plot design (after USDA, 2010). One plot is composed of 4 subplots, each with a fixed radius of 7.3 m, in which the Phase II data is collected. Distance between the subplot centers is 36.6 m horizontal distance. The azimuth between the center of subplot 1 and 2 is 360°, between 1 and 3 is 120°, and between 1 and 4 is 240°.

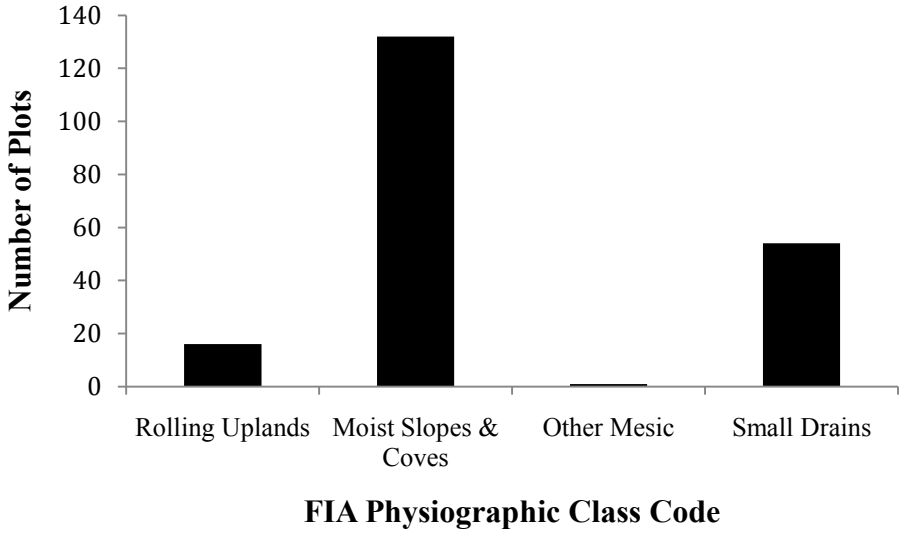

Fig. 2.3. The FIA-measured physiographic class code assigned to the study area plots (*n*=203).

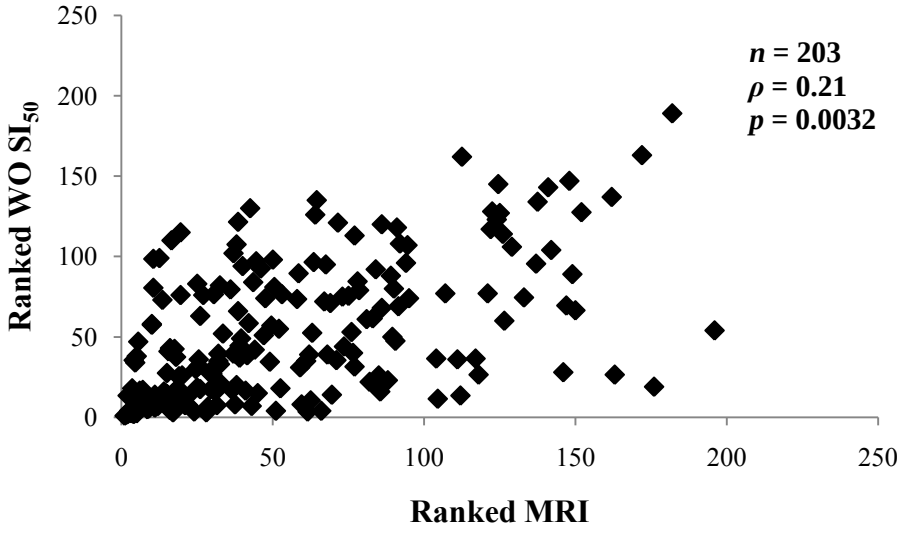

Fig. 2.4. Correlation scatter plot from Spearman's rank correlation test depicting the ranked values of the MRI and WO SI_{50} from 1 to 203.

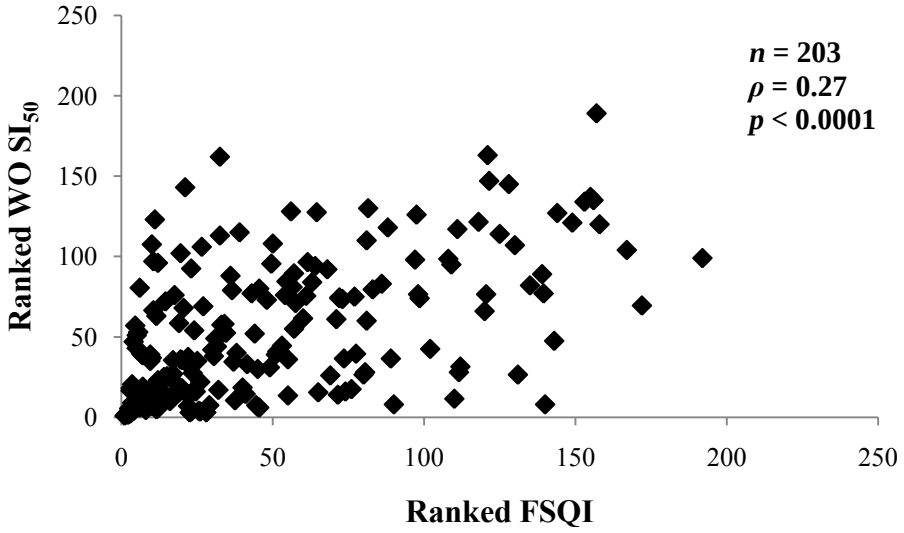

Fig. 2.5. Correlation scatter plot from Spearman's rank correlation test depicting the ranked values of the FSQI and WO SI_{50} between 1 and 203.

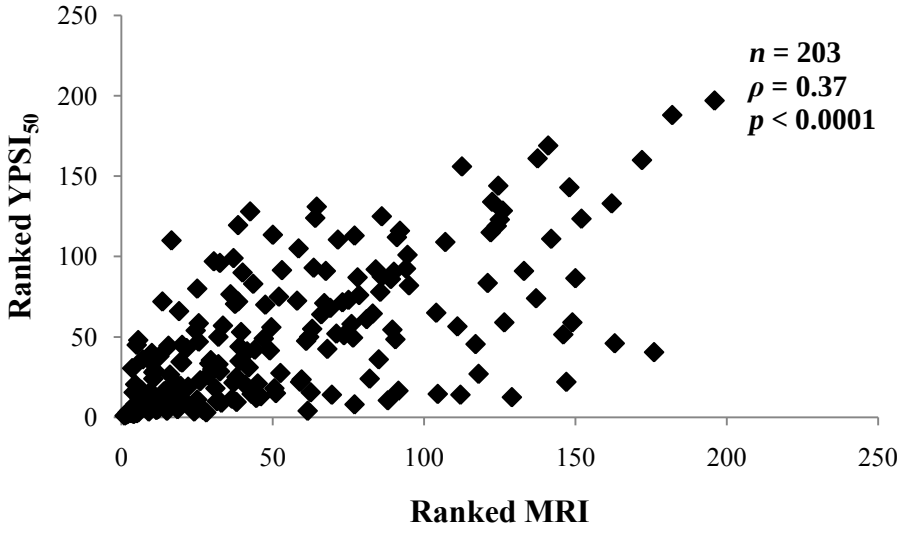

Fig. 2.6. Correlation scatter plot from Spearman's rank correlation test depicting the ranked values of the MRI and YP SI_{50} between 1 and 203.

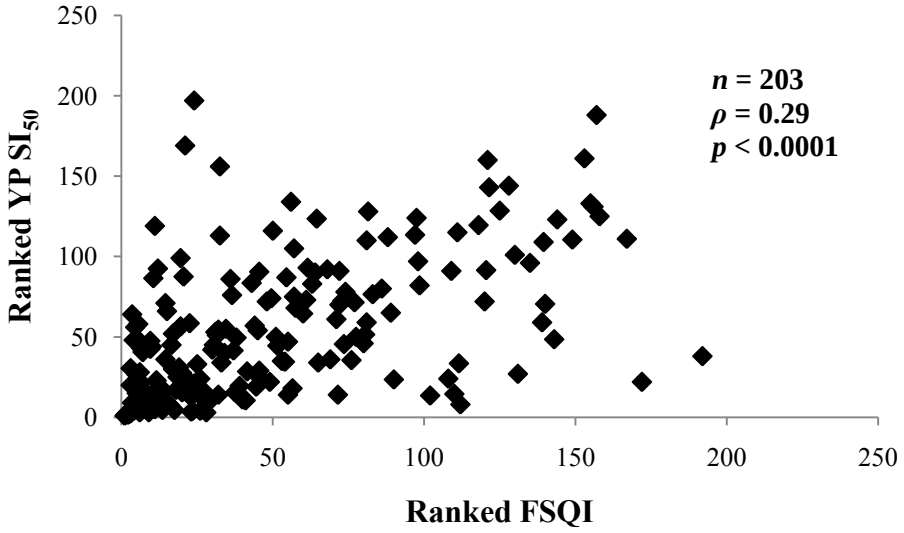

Fig. 2.7. Correlation scatter plot from Spearman's rank correlation test depicting the ranked values of the FSQI and YP SI_{50} between 1 and 203.

Chapter 3

Identifying Colluvial Soils in the Ridge and Valley to Refine Measures of Upland Hardwood Site Quality in the Southern Appalachians

1. Introduction

When a land manager is tasked with the job of parsing the landscape into management units, they seek to identify the forested sites of highest quality so that more intensive management can be applied to these areas for the highest potential return on their investment. Forests are usually managed for multiple benefits that include timber production, wildlife habitat, recreation, and aesthetics. Management efforts for timber production need to be focused on forested land of high site quality, because timber quality and quantity are directly related to site quality. Forests formerly used for timber products are being converted to other uses. As a result, site-specific forest management is needed where sites best suited for timber production are identified and managed intensively (Sedjo and Botkin, 1997). Methods to accurately identify site quality must be improved so that sites with the highest potential productivity can be identified and mapped. If these sites receive the most intensive management, sites better suited for other purposes, such as water protection, wildlife habitat, recreation, or wilderness can be managed to optimize these values. This could increase the efficiency with which we utilize our forests and reduce the commercial land base used for timber production.

Soil characteristics, especially depth and texture, have been found to correlate with hardwood site quality. Callaway et al., (1987) found that soil water holding capacity influenced the discrimination of twelve forest types in the Great Smoky Mountains. Fralish (1994) reported a decrease in hardwood basal area and site index (SI) with a decrease in soil volume for water storage. Where shallow soil profiles exist, as in the study area, a decrease in the soil water storage is especially significant to forest productivity (Childs et al., 1986). Baker and Broadfoot (1979) devised a field classification for several commercially important southern hardwoods based on the physical, moisture, nutrient, and aeration properties of the soil to assess the potential productivity of a site. Jones (1987) stated that it was too difficult to distinguish between the very best and other levels of site quality based on stand and tree measures alone. As

a result, Jones and Saviello (1991) developed a way to determine site quality for hardwood growth based on slope position and soil characteristics, such as texture, stoniness, and depth. More recently, Iverson (1997) developed a GIS-driven integrated moisture index (IMI), based on flow accumulation, curvature, hillshade, and the total water holding capacity of the soil, that explained 64% of the variation found in upland oak SI within stands on the Allegheny Plateau.

In the previous chapter, it was reported that species composition and topography could be used to identify sites of higher quality on predominantly residual soils in the upland hardwood forests of the Blue Ridge Mountains in North Carolina. The Moisture Regime Index (MRI) (McNab and Loftis, in press) and the Forest Site Quality Index (FSQI) (Meiners et al., 1984) were significantly correlated to recent SI measures derived from the Forest Inventory Analysis (FIA) database. The MRI and FSQI each accounted for roughly one-third of the variance of site quality in the Blue Ridge.

Upland hardwood tree species have different site requirements, and the MRI uses species composition to represent of the quality of a forested site based on the average moisture regime value of the species present (see Appendix C). Across a wide range of ages and species, the previous study found a significant and positive correlation between the MRI and yellow-poplar (*Liriodendron tulipifera* L.*)* SI (n=203, ρ=0.38, p<0.0001), as well as between the MRI and white oak (*Quercus alba* L.*)* SI (n=203, ρ=0.21, p<0.0001) in six counties in the Blue Ridge. Where site-demanding species occur, there is usually abundant available moisture for tree growth. Foresters have long recognized that certain tree species can indicate site quality through moisture, fertility, or temperature preferences. The MRI values were classified as xeric (1.0-1.9), subxeric (2.0-2.5), submesic (2.6-3.0), and mesic (3.1-4.0).

In the same study yellow-poplar SI and white oak SI were significantly correlated to a GIS-derived index of site quality, the FSQI (n=203, ρ=0.29, p<0.0001; n=203, ρ=0.27, p<0.0001, respectively). The combination of aspect, slope percent, and slope position create a landform that either retains or sheds water, to varying degrees. The FSQI was designed to capture these qualities of the landform and translate it to an estimate of site quality based on water availability (Meiners et al., 1984). In landscapes that have a low FSQI value, soils may be

shallower and hold less water, temperatures may be higher, evapotranspiration may be higher, and site quality could be less overall (e.g., Stephenson and Mills, 1999). The results from Chapter 2 suggest that where accurate measures of site quality do not exist or cannot be measured directly, there may be two alternatives. If a tree inventory is available the MRI can predict site quality based on species composition. A second approach may be to delineate site quality by modeling the FSQI with a 10 m DEM, which is from a database available for public use. These results indicate that topography can be used to predict site quality, but there are instances where soil depth can be useful in the estimation.

The oak-dominated hardwood forests of the central Ridge and Valley physiographic province in southwestern Virginia are found on long parallel mountains that typically have steep sideslopes and shallow soils. During the late Paleozoic, the mountains of the Ridge and Valley were formed as a result of the Alleghenian Orogeny. When the continents of North America and Africa collided, the bedrock in the Ridge and Valley was uplifted, folded, and tilted to vertical. Over time these layers have experienced differential erosion from the composition of the exposed rock. This has resulted in a region of long, parallel, low-elevation mountains with sandstone and shale ridges and eroded valleys of limestone (Fenneman, 1938).

The valleys were cleared long ago for agricultural use because of their relatively flat topography and fertile soil. Most of these areas are privately owned. In contrast, most of the ridges remain in forests because they have steeper slopes and poorer soils. Many of the ridges in this region are capped by the Tuscarora Sandstone member, which is very resistant and weathers to soils that are generally rocky, droughty, thin, and nutrient poor. Much of this land is under federal ownership as part of the Jefferson National Forest. The forests that dominate this landscape are xeric to subxeric Appalachian oak stands that, on average, do not have the capacity to support site-demanding species. Scarlet (*Quercus coccinea* Muenchh.), chestnut (*Q. prinus* L.), black (*Q. velutina* Lam.), and white oaks dominate the species composition, and site quality tends to be fairly low overall (Braun, 1950).

However, colluvial deposits occur at some locations on the sideslopes of the mountains. Colluvium is a surficial deposit, often found on sideslopes and foot slopes. It does not weather

from the underlying bedrock, rather it originates upslope and is transported down slope by gravity through the processes of creep, sliding, slope wash, windthrow, and debris flows (Mills, 2005). Colluvial deposits may also be the result of recent slumps and rock slides. It is often loose, non-stratified, poorly sorted, and heterogeneous (Leopold and Volkel, 2007). There are distinct differences in topography, soil properties, site quality, species composition, and tree quality on colluvial soils compared to residual soils on sideslopes in the Ridge and Valley. Due to the increased soil depth and higher site quality, certain mesic indicator species, such as yellow-poplar, have been observed to occur on these deeper colluvial soils on the sideslopes. A topography-based model of site quality, such as the FSQI, would not distinguish these areas of higher site quality from the surrounding subxeric forests. Because of this, there was an interest to investigate indicator species or topographic signatures that could distinguish the more productive colluvial soils from the residual soils on the sideslopes of the Ridge and Valley. In this study the terms of colluvium, colluvial soils, and colluvial deposits may be used interchangeably. As well, the terms residuum and residual soils represent a soil that has weathered in place.

The study area was chosen for two reasons. By allowing a control on topography, the long mountains and parallel sideslopes of the Ridge and Valley provided a unique opportunity to investigate site quality differences due to soil depth. Further, accurate maps of colluvial soils and deposits were available within the study area to develop and test predictive models (Schultz, 1986).

The objective for this study was to determine how to easily identify colluvial soils in the central Ridge and Valley of southwestern Virginia. The goal is to use these results as a management tool where accurate maps of soils and site quality do not exist. Two hypotheses were tested to accomplish this objective. First, on the linear sideslopes of the Ridge and Valley, where site quality is typically low in stands with subxeric to xeric moisture regimes, it was proposed that vegetation and topography could be used to identify colluvial soils. This was determined with data collected from a field study. A second hypothesis sought to determine if the topographic signature of colluvial soils could be identified in a geospatial information system (GIS) by modeling slope change on a digital elevation model (DEM) of the study area.

2. Methods

2.1 Study area

The study was conducted in the upland hardwood forests of the Jefferson National Forest within four counties in southwest Virginia (Fig. 3.1). The majority of the plots of this study were located in Giles and Craig Counties, Virginia, with the remainder being found in northern Montgomery and Roanoke Counties, Virginia.

Bailey (1995) described the area as the Central Ridge and Valley section of the Eastern Broadleaf Forest (Oceanic) Province. The Natural Resource Conservation Service designated the area as the Southern Appalachian Ridges and Valleys (USDA, 2006). The terrain consists of long linear parallel mountains oriented in a northeast-southwest direction. Alternating bands of sedimentary rocks, including sandstones, siltstones, shale, and limestone, make up the parent material. Over time, differential erosion, mass wasting, and deposition have formed the relatively low ridges and narrow valleys that make up the region (Bailey, 1995).

Soil orders in the study area are primarily Ultisols and Inceptisols with an udic moisture regime (USDA, 2006). Ultisols are strongly leached, highly weathered, acid forest soils with relatively low fertility often found on older, stable landscapes (Brady and Weil, 2002). Inceptisols are young soils that have minimal horizon development, and are often shallow to resistant bedrock, such as sandstone (Brady and Weil, 2002). Commonly found on steep slopes, Inceptisols may also be found on young geomorphic surfaces and resistant parent materials; therefore, they are unsuitable for agriculture and are often used for forestry, recreation, and watershed purposes. This part of Virginia has an udic soil moisture regime, indicating that soil moisture is high enough to meet plant needs throughout the year on average (Brady and Weil, 2002).

Soils in residuum of sandstone and shale on the sideslopes are typically mapped as a complex of the Berks-Weikert series. The Berks series is classified as a loamy-skeletal, mixed, active, mesic Typic Dystrudept (Soil Survey Staff, 2010). Similar but not as deep is the Weikert series, a loamy-skeletal, mixed, active, mesic Lithic Dystrudept (Soil Survey Staff, 2010). Soils in colluvium of acid sandstone, shale, and siltstone on the sideslopes are often mapped as the

Jefferson series. This soil is classified as a fine-loamy, siliceous, semiactive, mesic Typic Hapludult (Soil Survey Staff, 2010). The most common colluvial soil encountered within the study area was the Laidig series, a fine-loamy, siliceous, active, mesic Typic Fragiudult (Soil Survey Staff, 2010).

Elevations within the study area range from 321 to 1329 m above sea level. Climate is temperate, with mean annual temperature ranging from 11 to 17 ^{O}C. Mean annual precipitation ranges from 920 to 1400 mm (Bailey, 1995).

The forest vegetation of the study area is mostly subxeric Appalachian Oak forest, dominated by scarlet, chestnut, black, and white oak with an ericaceous understory. Uncommon and scattered pockets of mesic spruce-fir forest are found at the highest elevations, whereas cove positions support species such as yellow-poplar, black cherry (*Prunus serotina* Ehrh.*),* yellow birch (*Betula alleghaniensis* Britton*),* cucumbertree [*Magnolia acuminata* (L.) L.], and American Beech (*Fagus grandifolia* Ehrh.*)* (Braun, 1950).

2.2 Colluvium in the study area

The U.S. Geological Survey (USGS) has reported within the study area the presence of very old large slope failures, which are the origin of the some of the colluvial soils and deposits addressed in this study (Schultz, 1986). These anomalous landforms are not limited to the study area, but they are some of the largest known in the Appalachians. Slope differences between uphill and downhill slope positions, linear benches, and isolated knobs characterize the topography of weathered colluvium found on these mountains (Fig. 3.2) (Schultz, 1986). The colluvial deposits within the study area, on average, are smaller than those described by Schultz (1986), but some are quite large, particularly those found on the north slope of Butt Mountain in Giles County, Virginia. In a study in the Mountain Lake Area, Giles County, Virginia, Mills (1988) differentiated the colluvial deposits by age and location. Younger, less weathered colluvium was found close to the drainages and on steep slopes, and still had an abundance of boulder sized material. Older, more weathered colluvium was found on gentle nose slopes, hilltops, and above the drainages (Mills, 1988). Of particular importance to this study, Mills also

gave evidence that the colluvium could reach thicknesses up to eight m, as seen in road cuts (1988).

2.3 Field study to identify vegetation and topographic signatures of colluvium

2.3.1 Selection of plot locations

A 10 m DEM was obtained from the USGS National Elevation Dataset (Gesch et al., 2002; Gesch, 2007). From the U.S. Forest Service (USFS) we were able to gather GIS shapefiles of the forest management units, soil mapping units, geology, and roads for the study area. The detailed 1:50000 surficial geology and geomorphology map that depicted colluvial deposits within Giles County, Virginia, was digitized and used as another layer of mapped colluvium and residuum (Schultz, 1986).

Preprocessing of the DEM and the digital USFS soils map was necessary to control for topography and to locate the plots for the study. Slope position was delineated from the DEM and the sideslopes were extracted. Areas of colluvium, residuum, and non-target soils or deposits (i.e., alluvium) were separated on the USFS soils map. The sideslope grid was combined with the USFS soils map. A random point layer was generated, placed over the combined sideslope/soils grid, and 51 plots on colluvium were selected that were accessible. An adjacent site on a similar landscape position that was mapped as residuum was selected for each colluvial plot. The sideslope areas (and not the lower slope areas) were chosen because it is in this slope position that colluvial soils have the maximum difference and highest potential to affect site productivity in an otherwise sub-xeric environment.

2.3.2 Data Collection

2.3.2.1 Field Data

At each sample point, a plot was laid out according to Fig. 3.3. Plot center was established as the center of the central subplot. From that position was measured the basal area, using a 2.5 m^2 ha^{-1} BAF prism, and diameter at breast height to the nearest tenth of a centimeter for all overstory species within the prism plot, using a diameter tape. Four estimates of slope percent were measured using a clinometer: uphill, downhill, and on both sides following the contour of the land. The location of the plot was recorded from a GPS. Presence and type of

disturbance were recorded as binary variables. Disturbance was categorized into 3 categories for the database: gypsy moth, logged, and burned. Presence, size, and abundance of surface stones were observed. At a distance of 10 m from the plot center, three fixed-radius circular 1/4000th ha (1/100th ac) subplots were established at the azimuth values of 0, 135, and 225. A subplot of the same size was also established at the overall plot center. Understory species cover and frequency were recorded in the subplots.

2.3.2.2 Other data

Additional data from the plots were modeled from the DEM and GIS shapefiles and extracted to the field plot locations using ArcGIS 9.3 (Hillier, 2007). These included slope percent, aspect, slope position, elevation, forest type, stand age, primary parent material, curvature, soil series, the FSQI, and the Terrain Shape Index (TSI) (McNab, 1989). The source data of the grids used for the extraction of these variables may be found in Table 3.1.

Hydrological characteristics of the area were used to calculate a measure of slope position (summit, shoulder, backslope, toeslope, footslope, and floodplain) from the DEM. Two layers were developed that depicted downhill and uphill flow length between ridges and streams. The two flow length rasters were then used in the following algorithm:

$$\textit{Slope Position} = \textit{Downhill flow length} / (\textit{Uphill flow length} + \textit{Downhill flow length}) \qquad (1)$$

where *Slope Position* is expressed as a percent, *Downhill flow length* is calculated as the longest flow path, in meters, from each cell to a sink or outlet on the edge of a raster, and *Uphill flow length* is calculated as the longest upslope distance, in meters, along the flow path from each cell to the top of the drainage divide (Hillier, 2007). This calculation allowed for an estimate of slope position as a percent of the slope distance, where 0% slope position represented the bottom of the slope at stream edge and 100% was at the local ridge top. The final slope position was classified into six classes using the quantile option to guide the breaks. By comparing this final grid to the original DEM along with a digital raster graphic of the topographic map, positions on the final grid were classified into the six aforementioned slope positions.

In order to calculate the MRI, a tree list was created for each FIA plot and the MRI value was assigned to each tree species present within the plot (see Appendix C). These values were then averaged on a plot-level basis in the original equation (McNab and Loftis, in press).

$$MRI = (\Sigma\, a) / n \qquad (2)$$

where *MRI* is the plot-level Moisture Regime Index, $\Sigma\, a$ is defined as the sum of the MRI values for all species present within the plot, and *n* is the number of individual species within the plot. A modification was made to the original model to refine the index value for red maple (*Acer rubrum* L.*)*. Instead of using the original index value of 0, a value of 2.5 was assigned to this species. Although red maple does occur in a wide range of sites, it is most commonly seen in a subxeric environment in the study area, which would reflect a value 2.5. The MRI values were classified as xeric (1.0-1.9), subxeric (2.0-2.5), submesic (2.6-3.0), and mesic (3.1-4.0).

The FSQI was calculated in a GIS by reclassifying the aspect, slope position, and slope (%) grids to reflect the ordinal values (scores) originally assigned by the authors (Table 3.2) (Meiners et al., 1984). The reclassified grids were added to produce a final FSQI grid, which had a value range of 3 to 16. FSQI values were then used to predict upland oak SI values for all plots in this study (Table 3.3) (Meiners et al., 1982).

$$FSQI = AS + SLP + SLPS \qquad (3)$$

where *FSQI* is the plot-level Forest Site Quality Index, *AS* is the FSQI score of the GIS-derived aspect (degrees), *SLP* is the FSQI score of the GIS-derived slope (percent), and *SLPS* is the FSQI score of the GIS-derived slope position (percent).

The TSI provided a measure of the concavity or convexity of the landform on which a plot was located. Defined as the mean relative difference in elevation between the center of a plot and its boundary, the TSI generates positive values to indicate convex or water-shedding landforms (ridges, spur ridges, nose slopes), and negative values to indicate concave or water-holding landforms (creek beds, coves, bottoms). The original development of the model related

the TSI to yellow-poplar site index in the Blue Ridge.

No standard GIS algorithm has been developed to represent the TSI in a GIS. For this application it was determined, after working with several iterations, that the following algorithm best captured the TSI within the study area:

$$TSI = (P - A) \ / \ R \tag{4}$$

assuming a circular plot with a radius of 75 m, where *TSI* is the Terrain Shape Index, *P* is the elevation of the subject grid cell, *A* is the average elevation of grid cells at a radius *R* from the subject grid cell, and *R* is the radius in distance units, which was 75 m for this purpose. Depending on where the TSI is applied, the range of final values can vary, but they are always distributed around the value 0, which represents a planar slope. The TSI values for each plot were converted to yellow-poplar SI values using the original linear equation from McNab (1989), who was able to explain 51% of the variation between actual yellow-poplar SI and predicted yellow-poplar SI using the TSI:

$$\textit{Yellow-poplar } SI_{50} \ (m) = 53.6 \ (TSI) + 32.9 \tag{5}$$

Calculated variables for each plot included the MRI, basal area importance values for each overstory species, and the difference between the field-measured uphill slope (%) and field-measured downhill slope (%) (hereafter referred to as "field-measured slope difference"). Average slope was calculated from the field-measured uphill slope (%) and the field-measured downhill slope (%) for each plot. All variables measured for the study and their source may be found in Table 3.3.

2.3.3 Statistical analyses

Variables in the database were analyzed for normality and outliers using the Shapiro-Wilks test and box and whisker plots. To ensure that any differences found between the colluvial and residual plots were due to soil differences, *t*-tests were calculated on all variables to determine significant differences in variable means between colluvial and residual plots.

To determine any vegetative and topographic indicators of colluvium on sideslopes in the study area, logistic regression was used to fit predictors to the presence or absence of colluvium. Relative fit among the significant logistic models was analyzed with a stepwise procedure. Overall significance of the individual models was analyzed using the Hosmer-Lemeshow Chi-square test of goodness of fit. High *p*-values are desired for the Hosmer-Lemeshow, as this fails to reject the null hypothesis that the model's estimates fit the data adequately. Akaike information criteria (AIC) scores were analyzed among the models to determine which one best fitted the data.

To assess the accuracy of the model predictions, the distribution of prediction errors for new observations was estimated by bootstrapping, with the logistic models fitted separately to 13943 bootstrap samples and model predictions compared to observations that were excluded from the bootstrapped samples. Accuracy assessment of the models was calculated at different thresholds using the bootstrap samples. Receiver operator characteristic (ROC) curves were generated to depict the results of the accuracy assessments and to see if the models predicted colluvium better than by chance. SAS/STAT® Software Version 9.2 was used for all statistical analyses.

2.4 Geospatial study to identify the topographic signature of colluvium on a DEM

The observations of colluvium in the study area and on maps indicated that the upper boundary of the colluvial deposits often had a slope change where the transported colluvial material began and the original residuum ended (Fig. 3.2). Generally, the sideslopes covered in residual soils in the study area are uniformly steep, and where the colluvial deposits begin, one will often encounter a bench, or a flattening of the slope (Mills, 2005; Schultz et al., 1986).

2.4.1 The GIS model of slope difference

A GIS model was developed to capture this slope difference (hereafter referred to as "predicted slope difference"). The model functioned by determining the steepest uphill and downhill slopes in a specified neighborhood and taking the difference. The slope in a given cardinal direction was computed as rise/run, or difference in elevation between two cells divided by the distance between them. It was performed in ArcMap 9.3 using the focalsum function,

weighted by a kernel (Hillier, 2007). For example, the slope to the northeast in a 3 x 3 cell neighborhood was computed by multiplying the kernel values by the elevations in the corresponding cells and summing the products (Fig. 3.4). The result was arithmetically the same as dividing the difference in elevation by the distance between cells (14.142 m) and multiplying it by 100 (to convert to percentage). This focalsum operation was used for each of the eight cardinal directions with an appropriate kernel (set of weights), and then the maximum slope and minimum slope were obtained. Slopes uphill (from the center cell) were taken as positive and downhill slopes were taken as negative. Adding the maximum neighborhood slope and the minimum neighborhood slope resulted in high values where a steep uphill slope coincided with a near-zero downhill slope. The model was run for various neighborhoods of different sizes (3x3, 7x7, 9x9, 11x11, and 15x15 cells) using different sets of kernel files for each. Each run produced a separate grid that represented the slope difference at different spatial scales.

2.4.2 Statistical analyses

Spearman's rank correlation test was performed on the colluvial plots only to see if the predicted slope difference values were correlated to the field-measured slope difference values within the plots. For all neighborhood sizes, predicted slope difference means between colluvial and residual plots were tested for significant differences using *t*-tests. Slope differences may occur more often on colluvium versus residuum, but they may be at a scale that is bigger than what was modeled. To test this hypothesis, the slope difference grids created by the GIS model were compared to a grid that depicted non-target USFS soils and landforms (alluvial, colluvial, and residual soils on any landform except sideslopes), USFS colluvial soils on sideslopes, and USFS residual soils on sideslopes. This was done with zonal statistics within ArcGIS 9.3 (Hillier, 2007). The slope difference grids generated by the GIS model were also compared to the colluvial deposits on the digitized Giles County Geology Map (Schultz et al., 1986) with zonal statistics. The goal was to assess the mean predicted slope difference within these three types of soil/landform areas to see how, or if the mean predicted slope difference changed in relation to neighborhood size and soil type/landform.

3. Results

3.1 Field study to identify vegetation and topographic signatures of colluvium

3.1.1 Descriptive statistics

A total of 102 plots were established during the summer of 2009 (Fig. 3.1) (See Section *2.3.1. Selection of Plot Locations* in Methods). Fifty-one plots were located on sideslopes on colluvial deposits or colluvial soils. Fifty-one plots were established on sideslopes on neighboring residual soils. Twenty-five overstory species and 104 understory species were encountered and measured in the plots; however, those species that had less than 4 total observations were excluded from the model building dataset. This left a total of 13 overstory species and 49 understory species in the database. The majority of all plots occurred within the white oak/red oak/hickory USFS forest type (WO/RO/Hick). The second most prevalent forest type for the colluvial plots was the white oak/red oak/yellow-poplar forest type (WO/RO/YP); however, the second most prevalent forest type found in the residual plots was the chestnut oak/scarlet oak type (CO/SO).

Within all plots the most frequent geologic formation, as mapped by the USFS, was the Juniata Formation, which is composed primarily of sandstone and shale. The Tuscarora Formation, a highly resistant sandstone formation found on many of the caprocks of the mountains within the study area, was the second most prevalent geologic formation within all plots. Since colluvium is transported by gravity from another source, upslope geology for the colluvial plots was examined. By far the most common upslope geologic formation was the Keefer/Rose Hill/Tuscarora formation, composed of sandstone, shale, and conglomerate. The second most common formation was the Rocky Gap formation, which is pure sandstone.

Laidig cobbly fine sandy loam, 15-35% slopes, was the most commonly occurring soil series mapped in the colluvial plots. Laidig is classified as a fine-loamy, siliceous, active, mesic Typic Fragiudult (Soil Survey Staff, 2010). This soil, weathered from sandstone and shale colluvium, is typically found on benches and fan aprons in mountain environments. It is classified as very deep. Bailegap sandy loam, 15-35% slopes, was found most frequently in the residual plots. It is weathered from residuum sandstone and shale and is found on the ridges, hills, and hill slopes of uplands. It is classified as a fine-loamy, siliceous, semiactive, mesic Typic Hapludult (Soil Survey Staff, 2010). Site quality attributes for the four most common colluvial and residual soils within the plots may be found in Table 3.4.

Descriptive statistics indicated that, on average, plots were located on moderate slopes and at middle elevations for the study area (Table 3.5). A wide range of aspects was recorded. The average stand age for the colluvial plots was 68 years and the residual plots 76 years.

3.1.2 Tests of normality

The distributions of the sample means for the predictor variables were not normal, based on the Shapiro-Wilks tests. Box and whisker plots indicated the presence of outliers. These were removed, and subsequent examination of the data resulted in only the TSI distribution achieving normality. Because of this, it was decided to keep the outliers and analyze the data using the non-parametric method of Spearman's correlation and logistic regression.

3.1.3 Differences in environment and stand attributes between colluvial and residual plots

T-tests performed on all of the predictor variable means revealed significant differences in topography or stand attributes between the colluvial and residual plots. Significant differences were found in field-measured slope difference, average slope, the MRI, the FSQI, the TSI, yellow-poplar presence, and yellow-poplar basal area importance value (Table 3.6). These results indicated that compared to the residual plots, the colluvial plots were slightly less steep and had a higher field-measured slope difference. The landscape was less convex in the colluvial plots than the residual plots as indicated by the significant difference in the TSI. Taken as a whole, the differences in topography were also reflected in the significant differences of FSQI. Colluvial plots had more yellow-poplar basal area and site-demanding species, as reflected by the significant difference in the MRI.

3.1.4 Predicting colluvium with vegetation and topography

Logistic regression of the predictor variables against the presence or absence of colluvium on sideslopes in the study area suggested that colluvium was a function of three covariates: the yellow-poplar basal area importance value (hereafter referred to as "yellow-poplar BA"), the MRI, and the TSI (Table 3.7). Yellow-poplar was the only overstory species out of 25 to be associated with colluvial deposits on sideslopes in the study area. No understory species were found to be associated with the presence of colluvium. As seen in Fig. 3.5a, as the amount of yellow-poplar BA increased in proportion to the total basal area within a plot, so did

the probability of being on colluvium. On average, the yellow-poplar basal area importance value within the colluvial plots was approximately 18 times higher than what was found on average in the residual plots (Fig. 3.6).

There was a positive relationship between the probability of being on colluvium and the MRI values in the study area (Fig. 3.5b). Figure 3.7 details the breakdown of MRI scores between the colluvial and residual plots. On sideslopes in the study area, the number of residual plots with xeric to subxeric moisture regimes was higher than the number of colluvial plots in the same categories. However, this trend reversed when the submesic and mesic categories were examined, where there were more colluvial plots versus residual plots.

A final predictive model of colluvium that only considered topographic predictors revealed a significant negative relationship to the TSI. The probability of colluvium increased as TSI values decreased (Fig. 3.5c). Negative TSI values indicated concave landforms, so as the landscape became more concave on a sideslope, the probability of colluvium increased.

3.1.5 Accuracy assessment of the predictive colluvium models

Results of the Hosmer-Lemeshow Chi-square test of goodness of fit indicated that all three predictive models of colluvium were significant. AIC scores indicated the best predictor model of colluvium among the three models to be driven by yellow-poplar BA, followed by the MRI, then the TSI (Table 3.7).

The total number of hectares of colluvial soils on sideslopes that were mapped by the USFS in the study area was 11819 ha, or 11% of the total hectares of soil mapped by the USFS within the study area. There were 73610 ha of residual soils mapped by the USFS on sideslopes in the study area, or 70% of the total USFS mapped area within the study area. Predicted probability values generated from the bootstrap samples indicated the yellow-poplar BA model to have a prediction accuracy of 68% at a 60% threshold (Table 3.8). The basis of inference for these models is limited by the sample design. In other words, if a land manager knows that there is an 11% random chance of being on colluvium on a sideslope, then knowing the percentage of yellow-poplar BA on a site will allow him or her to predict the probability of being on

colluvium. If the model predicts a probability of colluvium that is 0.60 or more (i.e., the 60% threshold) then 68 out of 100 times the model will predict accurately, within the stated assumptions. The ROC curve indicated that this model predicted colluvium better than chance, which would is indicated by a straight diagonal seen in Fig. 3.8. In this example, 68% of the area is beneath the curve, which indicates more true positive responses versus false positive responses.

The MRI model achieved an accuracy of 71% at a 60% threshold (Table 3.9), which produced the ROC curve seen in Fig. 3.9. The highest accuracy that the TSI could achieve was 58% at a 50% threshold (Table 3.10). That is, in the study area where there was a 11% chance of being on colluvium, if the model predicts a probability for colluvium of 50% or more, then 58 out of 100 times it will be accurate within the study area. The ROC curve for the TSI model accuracy assessment is depicted in Fig. 3.10.

3.2 Geospatial study to identify the topographic signature of colluvium on a DEM

3.2.1 Predicted slope difference compared to field-measured slope difference

Spearman's rank correlation test on the colluvial plots (n=51) indicated no significant correlations between the predicted slope difference values and the field-measured slope difference values. Within the colluvial plots, the 11 x 11 cell neighborhood (110 x 110 m on the landscape) had the highest correlation to field-measured slope difference (ρ=0.14), but it was not significant (Table 3.11). T-tests revealed no significant differences in predicted slope difference means between colluvial and residual plots (Table 3.12).

3.2.2 Predicted slope difference compared to mapped colluvium and residuum on sideslopes in the study area

Zonal statistics generated for predicted slope difference values within zones of USFS colluvial soils on sideslopes showed an increase in mean predicted slope difference with an increase in neighborhood size (Table 3.13). No such increase was seen in the residual soils on sideslopes.

4. Discussion

4.1 Field study to identify vegetation and topographic signatures of colluvium

Anecdotal evidence of the forest types found within the study plots suggested a difference in site quality between the residuum and colluvial plots. The most common forest type overall was the WO/RO/Hick, which would be categorized into a subxeric moisture regime. However, the fact that the second most common forest type in the colluvial plots was WO/RO/YP and in the residual plots was CO/SO suggested a large difference in site between the two.

Yellow-poplar is a very site demanding species and achieves its best growth on deep, well-drained, loamy soils (Beck, 1990). Because of the moisture requirements, this species is commonly found in protected cove positions, but outside of these sites, it may also be found on gentle, concave slopes, characteristic of the colluvial soils of the study area (Beck, 1990). Conversely, scarlet oak was common on the driest sites in the study area. They are shade intolerant and compete successfully in a moisture-limited environment. They are often found on the gravelly, thin soils that are common on the sideslopes of the Ridge and Valley. The sites where these two species can successfully compete do not overlap as a general rule.

4.1.1 Differences in environment and stand attributes between colluvial and residual plots

Significant differences in environment between the colluvial and residual plots were somewhat expected, since it is known that colluvial deposits on sideslopes can form a profile-viewed wedge with the maximum thickness in the center (Ciolkosz et al., 1990). This same characteristic can produce a change in slope percent at the upper boundary of the colluvial deposit where it meets the original residuum material (Fig. 3.2) (Schulz, 1986). In the study area, colluvial plots were sometimes found on terrace-like areas within the sideslopes, which created a sharper slope change on the upper boundary of the plot. The slopes of the residual plots were typically straighter and steeper. Between the colluvial and residual plots, slope shape was significantly different, represented by the significant difference in the TSI. Colluvial plots tended to be more concave than convex, which may help explain why there was more yellow-poplar on these plots.

4.1.2 Predicting colluvium with vegetation and topography

Yellow-poplar BA, the MRI, and the TSI were found to be significant predictors of colluvium on sideslopes in the study area. Studies have consistently related the productivity of yellow-poplar to soil depth and good sites. Mumm and Vimmerstedt (1980) found a significant correlation (p=0.05) between the height of yellow-poplar and depth to restriction on the Allegheny Plateau in southeast Ohio. Across 540 plots in Indiana, West Virginia, and Ohio, Carmean and Hahn (1983) reported that yellow-poplar consistently had a higher SI at 50 years on good to excellent sites versus the oak species [black, white, scarlet, chestnut, and Northern red (*Q. rubra* L.)] present within the same plots. The same study showed that oak species outcompeted yellow-poplar on poor sites. Yellow-poplar is commonly used as an indicator species due to its sensitivity to slight changes in site quality (Hicks and Frank, 1984). The results seen in Fig. 3.6 were striking. It was clear that yellow-poplar was much more abundant on the colluvial soils than the residual soils. Yellow-poplar is not normally found on sideslopes unless the soils are sufficiently deep. These findings suggest that the yellow-poplar found on the colluvial plots on sideslopes in the study may indicate deeper soils that contribute to higher site quality.

The positive relationship depicted in Fig. 3.5b suggested that high MRI scores were associated with an increased probability of being on colluvium. The increased depth and increased water holding capacity of the colluvium on the sideslopes tended to support a species assemblage that was more moisture demanding, which was captured by the MRI. McNab et al. (2004) found that yellow-poplar and black locust (*Robinia pseudoacacia* L.), both found more often on colluvium than residuum in this investigation, were indicator species of site quality based on moisture in the Blue Ridge. This supports the idea that colluvium on sideslopes, being related to mesic indicator species, may be indicative of higher quality sites in an otherwise subxeric landscape. Figure 3.7 lends evidence to this idea as well, as it shows that on the extremes of moisture regimes on these sideslopes, that residual plots included a higher number of species that were adapted to a xeric to subxeric moisture regime, and colluvial plots included a higher number of species adapted to a submesic to mesic moisture regime. The MRI model would be most useful if a land manager had a tree list or current inventory available with which to calculate the MRI.

SI was not measured in the field because it was assumed that colluvial soils were more productive than residual soils. This is generally true, as in the case of the colluvial Jefferson soil series, which can exceed 200 cm in depth to restrictive feature (Table 3.4). However, the fact that the Laidig soil series was the most common soil within the colluvial plots may have biased the results lower. This series has a fragipan. Although fragipans may vary temporally and spatially, it may have restricted the rooting depth of trees in places. It also is known to have a perched water table in the summer (pers. comm., Tom Bailey, Soil Scientist, George Washington Jefferson National Forest). There are limits of the soils data used in this study, as well as in many mountainous areas in the southern Appalachians. Although the Laidig series was the most frequent soil found in the colluvial plots, it has been suggested that the original map may have been generalized to portray the most limiting soil in the area, and not the actual series.

Topography, through the TSI, also predicted the presence of colluvium on sideslopes within the study area. This model, while intuitive, did not fit the data as well as the MRI or yellow-poplar did. It could serve as a relatively simple starting point for the delineation of forest site quality on sideslopes through GIS modeling, should no other data, such as an inventory, be available.

4.1.3 Accuracy assessment of the predictive colluvium models

Initial analysis of the AIC scores for the yellow-poplar BA, MRI, and TSI models suggested that the yellow-poplar was the most robust of the three. While this may be true, the MRI may be more applicable in a management context, since it is based on numerous species versus one, as is the case with the yellow-poplar BA model. The MRI is simple in theory and execution, but powerful in expert knowledge. The TSI predicted slightly better than chance alone, which was a surprise. The TSI is intuitive, but difficult to reproduce accurately in a GIS environment, which may have contributed to the weak predictive model.

4.2 Geospatial study to identify the topographic signature of colluvium on a DEM

A spatial modeling approach was explored to see if a GIS could accurately predict colluvial deposits on sideslopes. Others have successfully modeled colluvium, but the studies often have been concerned with predicting slope failure versus predicting existing deposits (e.g.,

Schulz et al., 2008; Zhou et al., 2003). The idea for this study was to develop a GIS model that could identify the characteristic change in slope percent found on the upper boundary of a colluvial deposit. The slope differences predicted by the model did not significantly differ between the colluvial and residual plots. This could have been caused by a number of things. The model functioned by taking the steepest uphill slope and subtracting the steepest downhill slope within a specified neighborhood size. The caveat to this approach was that chosen slopes were not necessarily in a straight line perpendicular to the slope, which was how the uphill and downhill slopes were measured in the field. Further, the GIS slope change model did not take into account the size of the colluvial deposit below the inflection point of the upper boundary. So a plot could have been on colluvium, but not necessarily within range of the slope change. For instance, the mean size of a colluvial soil series mapped by the USFS within the study area was 11.49 ha. These soil polygons could be as small as 0.06 ha or as large as 463.86 ha, so the odds of capturing the exact slope change within one of these areas may have been too low given the approach. Additionally, the area of slope change is not always sharp, and the boundary between slopes may curve up and down the slope in response to microtopography (Gerrard, 1981).

Even though the field-measured slope difference within the plots did not correlate to the predicted slope difference, there was evidence that colluvial soils on sideslopes as a group did indeed experience a higher predicted slope difference than the residual soils. Zonal statistics indicated that within the colluvial soil polygons on sideslopes, the predicted slope difference on sideslopes increased as the size of the neighborhood increased. Residual soils showed no such increase, but rather stayed static as the neighborhood size increased (Table 3.13). Interestingly, the non-target landforms, composed mostly of ridges and waterways, had the highest increase in slope difference in relation to neighborhood size. These three trends reflect what is commonly seen in the field: that residual soils have no or slight slope differences on sideslopes, colluvial soils and deposits have moderate slope differences on sideslopes, and drainages and ridges have the steepest slope differences. This final trend was unexpected, since there was no thought about grouping the "non-sideslope" slope positions together, other than that they were non-target areas. It would be interesting to see if separation of these slope positions into logical groups (i.e., footslopes and toeslopes, drainages and ridges) would produce the same results as seen here.

Future modeling of colluvial topography on sideslopes may have greater success if the model accounts for the overall size of the colluvial deposit. There is definite utility to the GIS slope difference model and grids, but the approach to predicting small areas within large polygons needs to be refined.

5. Conclusion

The application of this study is management-driven. Site index is unreliable for use in most of the upland hardwood forests of the southern Appalachians due to disturbance, so we need other metrics that will provide accurate measures of site quality. For instance, in the previous chapter, 19% of the plots had to be eliminated from the working dataset due to either natural or silvicultural disturbance incurred since the last measurement. Additionally, the frequency of ice and snow damage to site trees may also restrict the use of the SI in the southern Appalachians. Research in the site quality of upland hardwoods suggests that landscape parameters are closely related to the productivity of a forested site. The fact that deep soils are productive is not new; however, developing tools to identify these deep soils in the absence of accurate maps is new. The results of this study present an opportunity to identify colluvial soils using vegetation and topography where accurate soils maps do not exist.

The next steps to improve upon this study include two suggestions. First, to identify colluvium more accurately in the Ridge and Valley, the MRI values of yellow-poplar could be increased to emphasize its strength as an indicator. Also, the use of remote sensing may hold promise in delineating colluvium in the Ridge and Valley. If imagery could be obtained that would show the spectral signature of yellow-poplar leaf out in the spring, the colluvium may be more accurately mapped.

If a tree inventory is available or a land manager has the time to go to the field, then the MRI or the abundance of yellow-poplar may be useful in delineating areas of colluvial soils and potentially, areas of higher site quality on sideslopes in the study area. The spatial modeling of the TSI holds promise and may be used for the same purpose. The advantage here is less fieldwork, but that comes with the price of less accuracy at this time. With these tools in hand, a

forest owner may manage the sideslope forests of the Ridge and Valley with better precision, higher efficiency, and greater potential return on investment.

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Table 3.1. All variables measured and used in the study and their source.

Variable	Source
Standing basal area (m^2)	Field measured
Diameter at breast height (cm)	Field measured
Uphill slope (%)	Field measured
Downhill slope (%)	Field measured
Sideslopes (%)	Field measured
Disturbance (binary/category)	Field measured
Surface stones (binary/category)	Field measured
Understory spp. cover (%)	Field measured
Understory spp. frequency (%)	Field measured
Overstory spp. presence	Field measured
Field-measured slope difference (%)	Calculated from field data
Average slope (%)	Calculated from field data
Aspect (azimuth in degrees)	Extracted from DEM
Curvature	Extracted from DEM
Elevation (m)	Extracted from DEM
Forest type	Extracted from USFS shapefile
Stand age (years)	Extracted from USFS shapefile
Primary parent material	Extracted from USFS shapefile
Soil series	Extracted from USFS shapefile
FSQI	GIS algorithm
TSI	GIS algorithm
MRI	Calculated from field data
Basal area importance values per spp.	Calculated from field data
Predicted slope difference (%)	GIS model

Table 3.2. Ordinal values assigned to variables in the FSQI model (after Meiners et al., 1984).

FSQI Value	Aspect	% Slope	Slope Position
1	196-260	>=60	Shoulder
2	166-195; 261-280	45 – 59	Backslope
3	146-165; 281-340	30 – 44	Summit
4	0-20; 341-360	15 – 29	Footslope
5	81-145	0 – 14	Toe Terrace Floodplain
6	21-80		

Table 3.3. Predicted upland oak SI values that correspond to the FSQI index values (after Meiners et al., 1984).

FSQI Value	Upland Oak SI_{50} *(m)*	FSQI Value	Upland Oak SI_{50} *(m)*
3	14	10	21
4	15	11	22
5	16	12	23
6	17	13	24
7	18	14	25
8	19	15	26
9	20	16	27

Table 3.4. Site quality attributes of the most common colluvial and residual soil series found within the plots (colluvial plots *n*=51; residual plots *n*=51) of the study area in the Ridge and Valley (from Creggar and Hudson, 1985; Soil Survey Staff, NRCS, USDA, 2010; Swecker et al., 1985).

Soil Series	Occurrence (*out of 51 plots*)	Landform	AWC* (*cm*)	Depth to Root Restrictive Feature (*cm*)	Common Trees**	Site Index (*m*)
Laidig cobbly fine sandy loam, 15 – 35% slopes						
Colluvium: sandstone & shale	13 (26%)	Fan apron, bench	10 - 91	Fragipan: 76 -127	NRO	20
Covers 2356 ha, or 2.25% of total USFS mapped area					WO	20
					EWP	21
Laidig cobbly fine sandy loam, 3 – 15% slopes						
Colluvium: sandstone & shale	11 (22%)	Fan apron, bench	10 - 91	Fragipan: 76 - 127	NRO	20
Covers 2011 ha, or 1.95% of total USFS mapped area					WO	20
					EWP	21
Jefferson loam, 15-35% slopes						
Colluvium: sandstone & shale	6 (12%)	Mountainside	19 - 152	> 203	NRO	23
Covers 1078 ha, or 1.03% of total USFS mapped area					YP	30
					VP	23
Jefferson loam, 3 – 15% slopes						
Colluvium: sandstone & shale	6 (12%)	Mountainside	19 – 152	> 203	NRO	23
Covers 1650 ha, or 1.58% of total USFS mapped area					YP	30
					VP	23
Bailegap sandy loam, 15 – 35% slopes						
Residuum: sandstone & shale	7 (14%)	Ridge, hillslope	17 – 140	Bedrock (lithic):	NRO	18
Covers 5574 ha, or 5.32% of total				102 - 152		
Berks channery silt loam, 15 – 35% slopes						
Residuum: shale & siltstone	6 (12%)	Mountainside	5 – 64	Bedrock (lithic):	NRO	18
Covers 2681 ha, or 2.56% of total				51 – 104	BO	18
					VP	18
Lily sandy loam, 15 – 35% slopes						
Residuum: sandstone	6 (12%)	Ridge, hillslope	8 – 61	Bedrock (lithic):	VP	20
Covers 5898 ha, or 5.63% of total				51 - 102	SO	20
					PP	20
Lily gravelly sandy loam, 35 – 60% slopes						
Residuum: shale & sandstone	6 (12%)	Ridge, hillslope	8 – 61	Bedrock (lithic):	VP	20
Covers 2780 ha, or 2.65% of total				51 - 102	SO	20
					PP	20

*Available water holding capacity

**NRO=Northern red oak (*Quercus rubra* L.), EWP = Eastern white pine (*Pinus strobus* L.), YP=Yellow-poplar (*Liriodendron tulipifera* L.), VP=Virginia pine (*P. virginiana* Mill.), PP=Pitch pine (*Pinus rigida* Mill.), BO=Black oak (*Q. velutina* Lam.), SO=Scarlet oak (*Q. coccinea* Muenchh.).

Table 3.5. Descriptive statistics of all field plots in the study (*n*=102).

	Colluvial plots (*n*=51)				Residual plots (*n*=51)			
Variable	**Mean**	**S.E.**	**Min**	**Max**	**Mean**	**S.E.**	**Min**	**Max**
Age (years)	68	4	5	120	76	4	18	110
Slope (%)	20	10	8	46	24	11	7	49
Aspect (^{o})	168	15	2	358	202	14	4	358
Elevation (m)	707	20	473	1100	726	21	446	1141
Field-measured slope difference (%)	4	1	-15	22	1	1	-17	13

Table 3.6. Significant differences in variable means between colluvial plots and residual plots as determined by *t*-tests (α=0.05).

Variable	*p*-value	Mean	
		Colluvial plots (*n*=51)	**Residual plots (*n*=51)**
Average slope (%)	0.05	20	24
Field-measured slope difference (%)	0.04	4	1
FSQI	0.03	10	9
MRI	<0.0001	2.1	1.8
TSI	0.02	0.01	0.03
Yellow-poplar basal area importance	<0.0001	0.14	0.01
Yellow-poplar presence	<0.0001	0.40	0.06

Table 3.7. Parameter estimates, fit statistics, and AIC scores for predictive colluvium models fitted with vegetation and topographic data from the study plots (*n*=102).

Variable	Parameter Estimate	S.E.	*p*-value	AIC Score
Yellow-poplar basal area Model:				
Intercept	-0.4537	0.2290	0.0475	122.63
Yellow-poplar BA Importance Value	12.3857	6.8454	0.0089	
MRI Model:				
Intercept	-4.8215	1.3399	0.0003	127.81
MRI	2.1957	0.6109	0.0003	
TSI Model:				
Intercept	0.1667	0.2166	0.4417	140.49
TSI	-10.6816	5.1012	0.0363	

Table 3.8. Prediction accuracy for the model P(Colluvium) = 1/(1+exp(-(-0.4537+12.3857 (Yellow-poplar Basal Area Importance Value))) at different thresholds (*n*=13943).

Threshold	False Positive Rate	True Positive Rate	Accuracy
0.20	1.00	1.00	0.51
0.30	0.92	0.96	0.53
0.40	0.46	0.70	0.62
0.50	0.08	0.44	0.67
0.60	**0.04**	**0.40**	***0.68**
0.70	0.03	0.36	0.66
0.80	0.02	0.31	0.64
0.90	0.01	0.26	0.62

*Highest prediction accuracy achieved by the model.

Table 3.9. Prediction accuracy for the model P(Colluvium) = 1/(1+exp(-(-4.8215+2.1957 (Moisture Regime Index))) at different thresholds (*n*=13943).

Threshold	False Positive Rate	True Positive Rate	Accuracy
0.20	0.94	0.97	0.52
0.30	0.77	0.89	0.56
0.40	0.51	0.74	0.61
0.50	0.23	0.59	0.68
0.60	**0.08**	**0.50**	***0.71**
0.70	0.05	0.35	0.65
0.80	0.03	0.20	0.59
0.90	0.01	0.09	0.55

*Highest prediction accuracy achieved by the model.

Table 3.10. Prediction accuracy for the model P(Colluvium) = 1/(1+exp(-(0.1667-10.6816 (Terrain Shape Index))) at different thresholds (*n*=13943).

Threshold	False Positive Rate	True Positive Rate	Accuracy
0.20	0.97	1.00	0.51
0.30	0.91	0.99	0.54
0.40	0.75	0.89	0.57
0.50	**0.42**	**0.58**	***0.58**
0.60	0.15	0.23	0.54
0.70	0.04	0.06	0.51
0.80	0.01	0.01	0.50
0.90	0.00	0.00	0.50

*Highest prediction accuracy achieved by the model.

Table 3.11. Spearman's correlation coefficients *(ρ)* and *p*-values between for all pair-wise relationships between the field-measured slope difference and the predicted slope difference for 5 different neighborhoods on colluvial soils on sideslopes in the study area (*n*=51).

Neighborhood*	**Correlation Coefficient *(ρ)* to field-measured slope difference**	***p*-value**
30 x 30 m	0.08	0.56
70 x 70 m	0.07	0.65
90 x 90 m	0.13	0.35
110 x 110 m	0.14	0.32
150 x 150 m	0.09	0.55

*Using a 10 m DEM

Table 3.12. Significant differences in predicted slope difference means for 5 neighborhoods between colluvial plots and residual plots as determined by *t*-tests (α=0.05).

		Mean	
Neighborhood*	***p*-value**	**Colluvial plots (*n*=51)**	**Residual plots (*n*=51)**
30 x 30 m	0.19	1.03	-0.79
70 x 70 m	0.21	0.41	-1.15
90 x 90 m	0.13	0.55	-1.68
110 x 110 m	0.13	0.60	-1.48
150 x 150 m	0.21	0.57	-0.82

*Using a 10 m DEM

Table 3.13. Zonal statistics for predicted slope difference within 5 neighborhoods and three USFS soils/landform areas within the study area; total acreage reflects only the mapped USFS soil polygons on public lands within the study area and not the entire study area. Positive values indicate a concave landform, or the difference between a steep upper slope and a shallow lower slope, and negative values indicate convex landforms, or the difference between a shallow upper slope and a steep lower slope.

	Non-target Land* (19295 ha)**			**Colluvial Soils** (11819 ha)**			**Residual Soils** (73610 ha)**		
Neighborhood*	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
30 x 30 m	-196	249	-3	-163	174	1	-238	200	1
70 x 70 m	-116	113	-7	-80	86	3	-113	124	1
90 x 90 m	-121	09	-8	-83	76	4	-108	110	1
110 x 110 m	-114	112	-8	-74	74	4	-105	109	1
150 x 150 m	-103	113	-8	-67	78	5	-111	101	1

*Using a 10 m DEM

**On sideslopes within the study area

***Consists of alluvium, colluvium, and residuum on ridges, shoulders, foot slopes, toe slopes, and floodplains

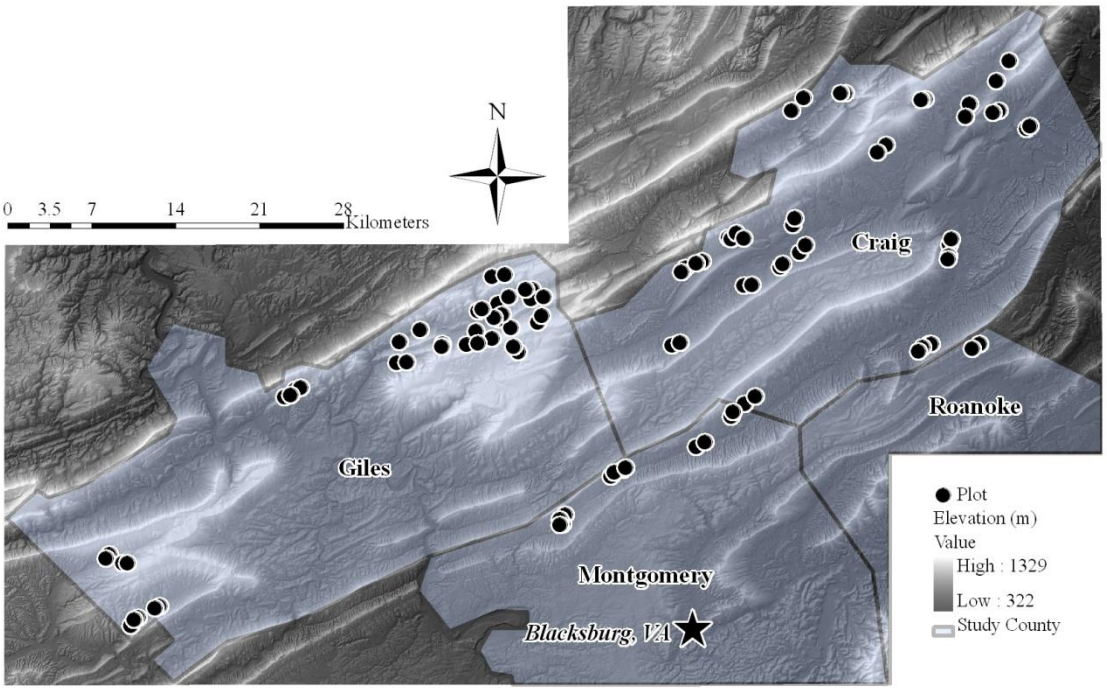


Fig. 3.1. Study area and plot locations within the central Ridge and Valley in southwest Virginia.

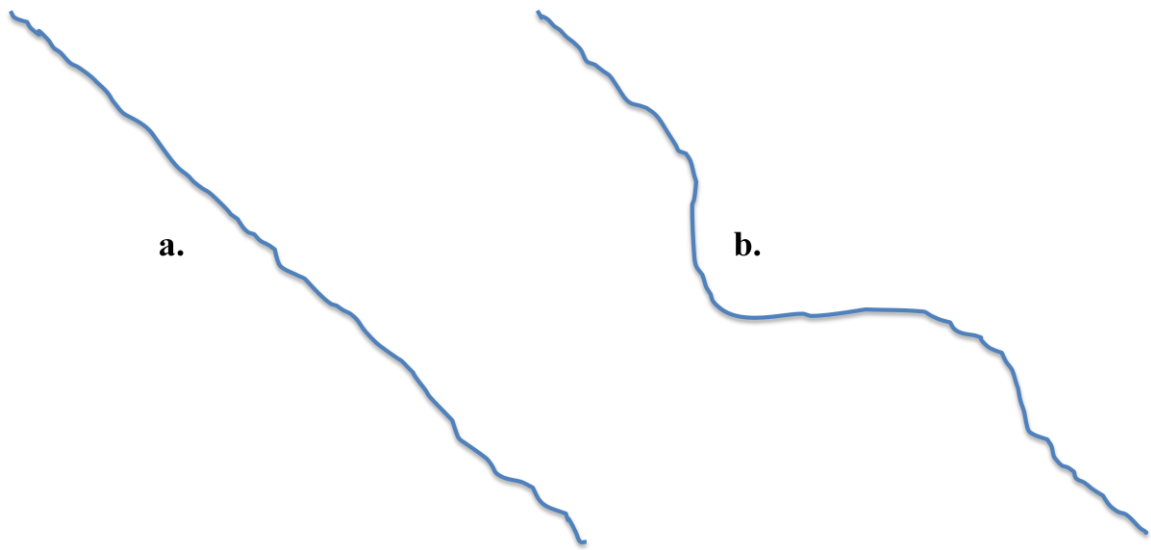


Fig. 3.2. Typical profile view of sideslopes in the study area on residual soils (**a.**) and colluvial soils (**b.**). Residual soils on sideslopes are usually planar and show no difference in slope percent between the upper slope position and the lower slope position. However, colluvial soils on sideslopes show a difference in slope between the upper slope position and the lower slope position caused by the accumulation of material transported from an upslope source.

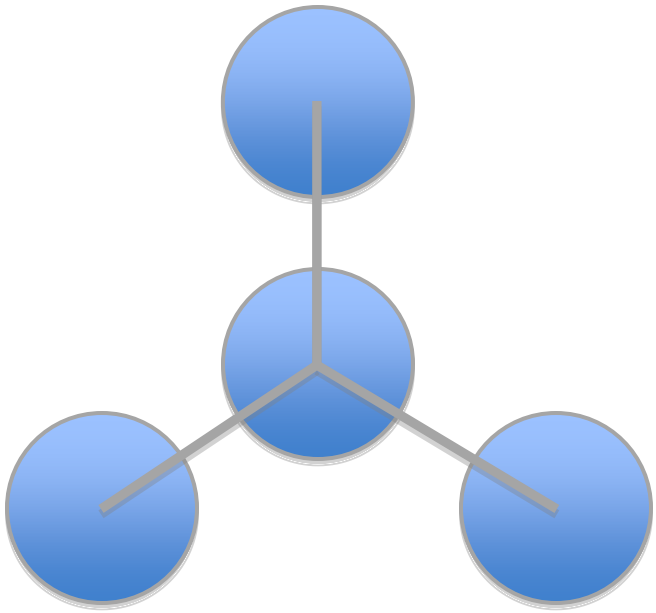
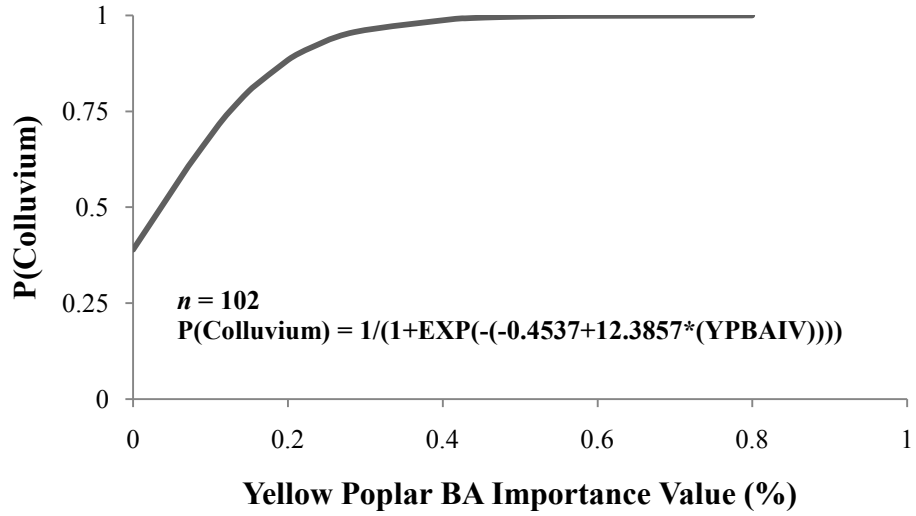


Fig. 3.3. Field plot layout: center sub-plot was 2.5 m^2 ha^{-1} BAF prism plot from which overstory species and topography were sampled; understory species sampled from 4-1/4000th-ha fixed radius subplots, which were separated by ½ chain, or 10 m.

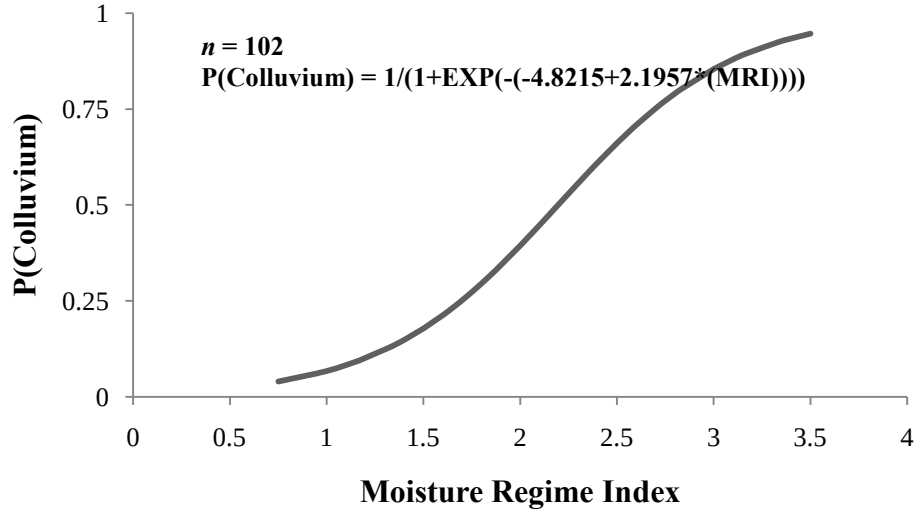
0	0	7.071
0	-7.071	0
0	0	0

Fig. 3.4. Example of a kernel used in the GIS algorithm to find possible colluvial sites in a DEM. The values shown in the cells are multiplied by elevation values in corresponding locations and summed. The result for the example above will yield the percent slope to the *northeast* for a 10m DEM (with positive values representing uphill slopes from the center cell).

a.



b.



c.

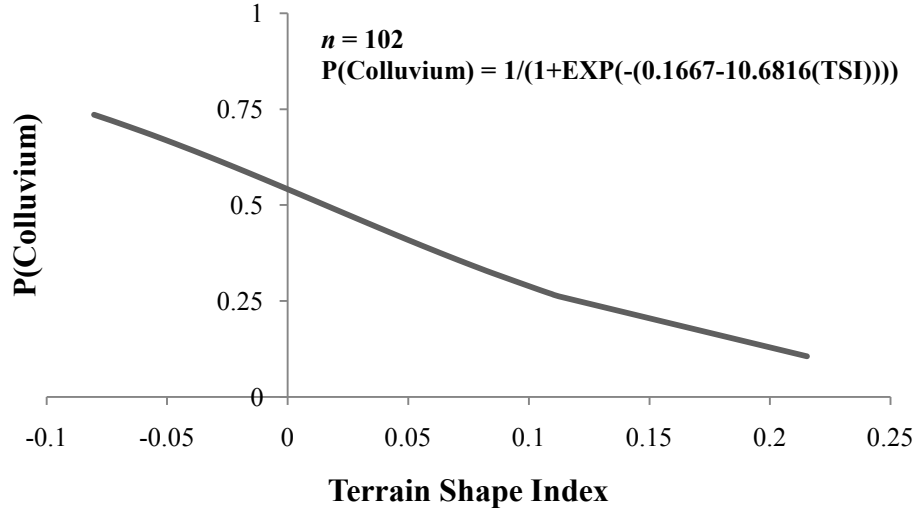


Fig. 3.5. P(colluvium) as a function of YPBAIV (**a.**), the MRI (**b.**), and the TSI (**c.**).

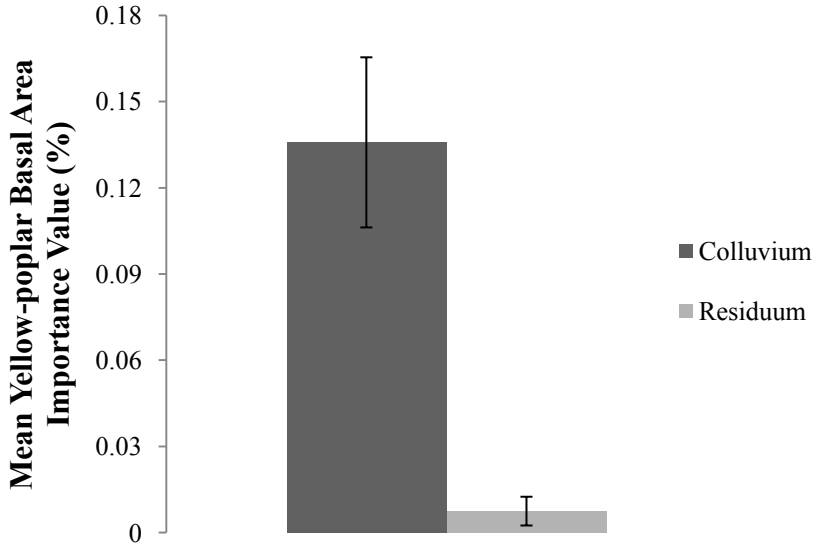


Fig. 3.6. Comparison of the mean yellow-poplar basal area importance value (%) and standard error between colluvial plots (*n*=51) and residual plots (*n*=51).

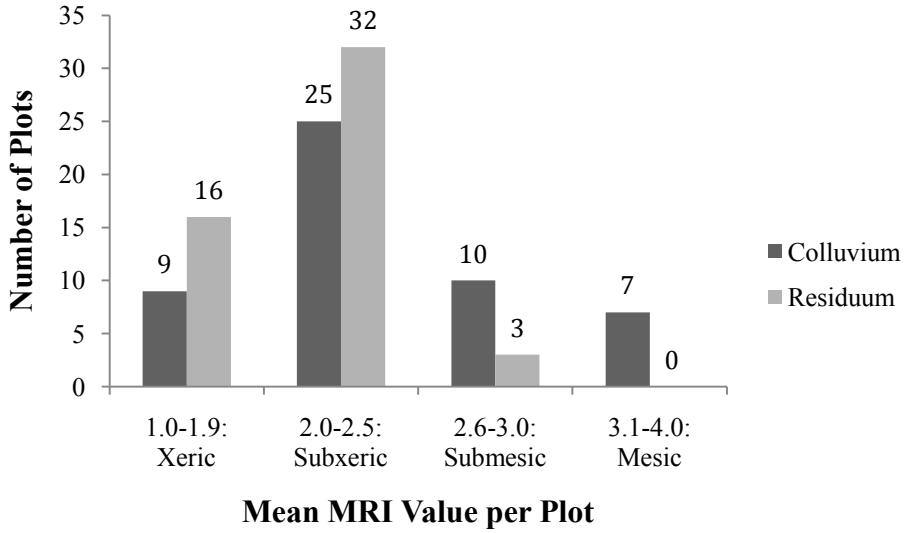


Fig. 3.7. Total number of plots found within four different MRI categories according to colluvium or residuum.

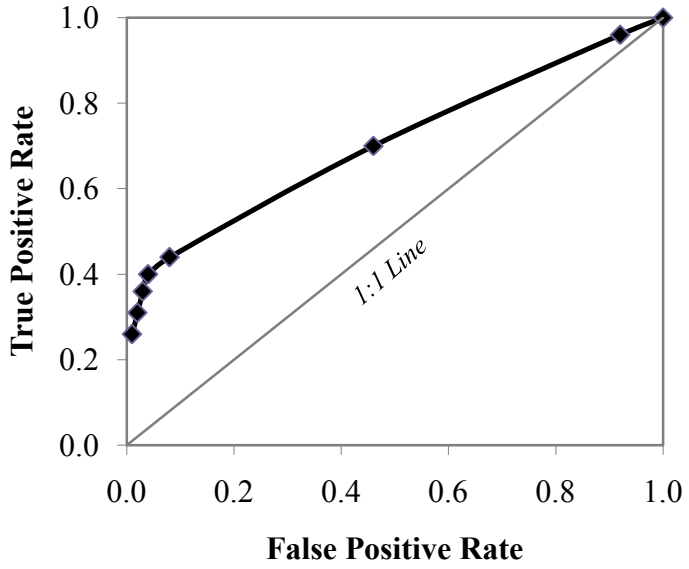


Fig. 3.8. Receiver operator curve representing accuracy assessment (*n*=13943) for the model P(Colluvium) = 1/(1+Exp(-(-0.4537+12.3857*(Yellow-poplar Basal Area Importance Value)))).

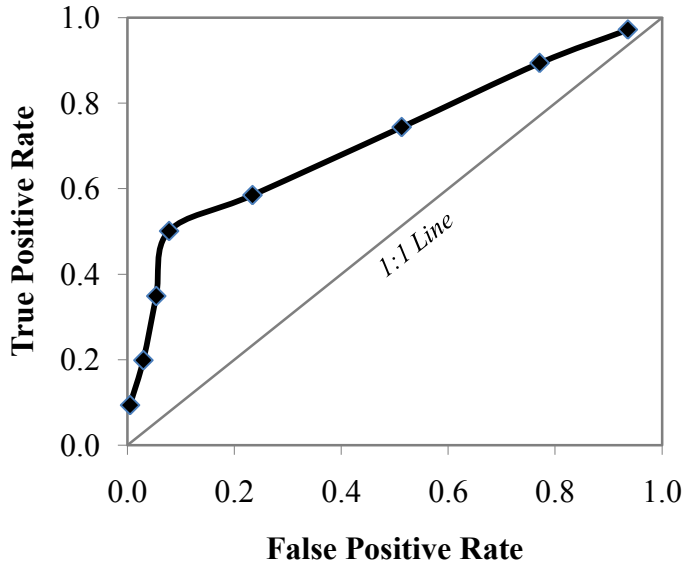


Fig. 3.9. Receiver operator curve representing accuracy assessment (*n*=13943) for the model P(Colluvium) = 1/(1+Exp(-(-4.8215+2.1957*(Moisture Regime Index)))).

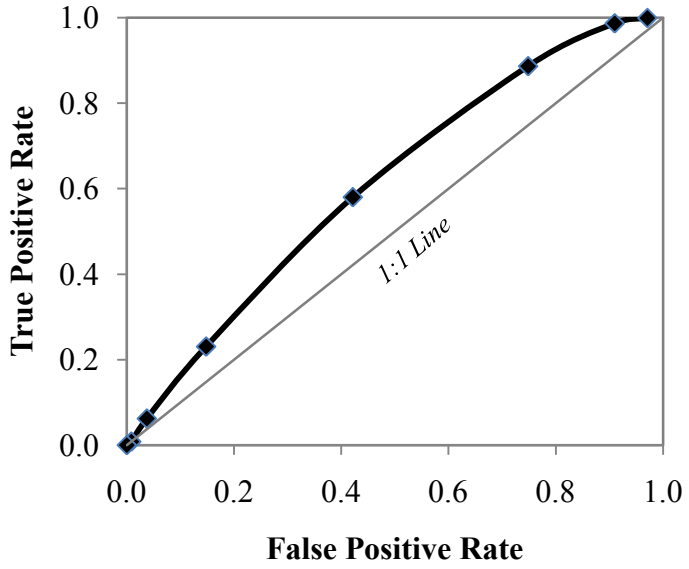


Fig. 3.10. Receiver operator curve representing accuracy assessment (*n*=13943) for the model P(Colluvium) = 1/(1+Exp(-(1.667-10.6816*(Terrain Shape Index)))).

Chapter 4

Predicting Upland Hardwood Site Quality in the Southern Appalachians as a Function of the Inputs, Supply, and Usage of Available Water

1. Introduction

Water is a significant factor that limits vegetation growth in the southern Appalachians (Smith, 1994). Within a forest, the water that is available for tree growth is determined by the supply and demand for the water. The supply includes the climatic inputs and the storage capacity of the soil, while the demand is driven mainly by the evapotranspiration rates of the vegetation. Brooks et al. (2003) defines the water budget as $ET + l = P - Q$, where ET is evapotranspiration, l is groundwater seepage, P is precipitation, and Q is change in storage (all units in mm). Research has shown that water availability can be a primary control on forest productivity (Vertessy et al., 1996), and can affect species composition across the landscape (Stephenson 1998).

The soil moisture gradient has long been recognized as an integral part of the water budget for its influence on the spatial variability of site quality, species composition, and forest growth. The soil moisture gradient is the spatial variability in soil moisture across a landscape (e.g., Yan et al., 2004). Whittaker (1956) and Day and Monk (1974) found that elevation and topography, proxies of the soil moisture gradient, explained the vegetation patterns in the mountains of western North Carolina, USA. White (1958) reported that the amount of soil moisture was the primary influence on any estimate of site productivity. Other studies have found that soil water-holding capacity, which is a function of soil depth, texture, and local topography, can be used to explain differences in forest composition and site quality (Stephenson and Mills, 1999). Carmean (1979) stated that soil, topographic, and climatic attributes could indirectly estimate site quality over large landscapes independent of the vegetation cover. The soil attributes he cited as influential were those that affected the amount of water the soil could hold, such as depth, texture, and stone content. Topographic features, such as aspect, slope position, slope percent, and elevation were included, as were the climatic features of annual

rainfall and temperature (Carmean, 1979). More recently, Iverson et al. (1997) directly related soil moisture to species distribution in southeast Ohio.

In the southern Appalachians, an analysis of the moisture of a site cannot be decoupled from the topography, as seen in some of the previous studies cited. The shape of the landscape and position on the hill slope will influence the flow and amount of water that is available for tree growth (Hack and Goodlett, 1960). Elliott et al. (1999) described soil moisture as a function of precipitation, terrain shape, and soil characteristics. Topographic variables, particularly elevation, slope percent, and aspect, have been repeatedly referred to as the most important determinants of site quality because of their influence on the site moisture regime (Carmean, 1975). Available moisture for plant growth, which is directly related to aspect, slope percent, and landform, is the single most important factor that drives site quality and productivity in the southern Appalachians (Smith, 1994). Topography and soil water holding capacity were found to be the primary controls on hillslope soil moisture during dry periods in the southern Appalachians (Yeakley et al., 1998). Fralish (1994) found that stand basal area was a function of the soil water reservoir, which was controlled by slope angle, aspect, slope position, and effective soil depth. Soil moisture has been tied to the topographic paradigm, which describes differences in growth parameters between northeast and southwest-facing slopes (Boerner, 2006). In the northern hemisphere, slopes with an aspect of north to northeast have higher moisture levels versus slopes with an aspect of south to southwest due to the higher amount of solar insolation incurred by the latter (Iverson et al., 1997). McNab (1989) was able to relate yellow-poplar (*Liriodendron tulipifera* L.*)* site index in the Blue Ridge Mountains to an index of the convexity or concavity of a landform, also known as the Terrain Shape Index (TSI). In the Ridge and Valley of southwest Virginia, the Forest Site Quality Index (FSQI) was developed as a field method to describe site quality and productivity based on aspect, slope position, and slope percent as they influence available soil moisture (Meiners et al., 1984).

Studies of forest productivity commonly analyze pattern or process, or infer one from the other. For example, elevation is often cited as a significant topographic predictor of site productivity and species distribution due to its relationships with precipitation and temperature. There is generally an increase in precipitation and decrease in temperature as elevation increases

(Lookingbill and Urban, 2004). McCay et al. (1997) reported a strong relationship between the secondary forests of eastern West Virginia and elevation. From a study of 258 plots within the Monongahela National Forest, they found that the presence of overstory species were primarily influenced an elevational gradient (McCay et al., 1997). Although it has already been cited, the work of Whittaker (1956) cannot be excluded from a conversation regarding the relationship between elevation and species distribution. While the studies cited have contributed greatly to the understanding of site quality in relation to topography and available water for tree growth, it is important to remember that elevation differences do not cause the distribution of forest species. Rather, the climatic variables that co vary with elevation, i.e. precipitation and temperature, are the influences that affect forest species distribution (Lookingbill and Urban, 2005).

In the upland hardwood forests of the southern Appalachians, management tools are needed that are based on the characteristics of the site to quantify the site quality where no accurate maps of site quality exist. In Chapter 2, it was reported that species composition and topography could be used to identify sites of high quality on a scale that is appropriate for stand-level management in the upland hardwood forests of the Blue Ridge Mountains in North Carolina. Despite the fact that available water supply was not significantly correlated to white oak (*Quercus alba* L.) site index at base age 50 in Chapter 2, we believe this parameter to be important. Chapter 3 indicated that deeper colluvial soils on sideslopes in the Ridge and Valley of southwest Virginia supported more site-demanding species, which suggested that these soils represented areas of higher site quality based on increased available water supply.

Up to this point, efforts within this dissertation have sought to predict site quality primarily using variables that represent the supply side of the water budget equation, such as topography and soil depth. In Chapter 2, the FSQI was significantly correlated to FIA-measured site index (SI) in the Blue Ridge. Assessing the supply, as well as the demand features of the water budget could produce a more accurate measure of site quality than what can be determined by topography alone. Therefore, the objective of this study was to determine if estimates of site quality in the Blue Ridge Mountains of North Carolina were related to the inputs, storage, and usage of water in the upland hardwood forests. Specifically, can measures of site index at base

age 50 be predicted by variables that represent the inputs, supply, and usage of the available water on the site? A second hypothesis tested if site quality classes could be predicted by a combination of topography and the long-term annual water budget, defined as the difference between long-term precipitation and long-term potential evapotranspiration.

2. Methods

2.1 Study area

The study was conducted in the upland hardwood forests within six counties located entirely within the mountainous Blue Ridge of western North Carolina (Fig. 4.1). Bailey (1995) described the area as being part of the Central Appalachian Broadleaf Forest Province. The Natural Resource Conservation Service has designated the area as the Southern Section of the Blue Ridge Province of the Appalachian Highlands (USDA, 2006). The terrain is heavily dissected and the parent material is composed of mostly crystalline and some sedimentary rocks. Primary soil orders include Inceptisols and Ultisols with an udic moisture regime (USDA, 2006). Elevations within the study area range from 205 to 2036 m above sea level. Climate is temperate, with mean annual temperature ranging from 10 to 17 ^{O}C and average annual precipitation ranging from 900 to over 2000 mm, the highest in the eastern U.S. The six counties cover approximately 780,000 ha, or 34% of the Blue Ridge within North Carolina.

Five distinct forest types prevail that are primarily controlled by a moisture gradient that changes with elevation and aspect. As a general rule, as elevation increases, one would sequentially encounter oak-pine forests, Appalachian oak forests, northern hardwood forests, and at the highest elevations, spruce-fir forests (Bailey, 1995). Aspect is an important determinant of forest communities as well, so that site-demanding species will often be found at higher elevations on north to northeast aspects and at lower elevations on south to southwest aspects. Remnants of mixed mesophytic forests may be found in the protected coves of the mountains where the soil and water accumulate.

2.2 General approach to data collection

Plots were extracted from the FIA database, along with selected landscape, site quality, location, and tree data from the plots. For each plot the soil mapping unit was identified within the Soil Survey and Geographic (SSURGO) database, and from this the available water supply was extracted (Soil Survey Staff, 2009). Additional landscape attributes and site quality indices were extracted from a 10 m digital elevation model (DEM). Long-term climate data were downloaded from the Daily Surface Weather and Climatological Summaries (Daymet) database (Thornton et al., 1997; Thornton and Running, 1999; Thornton et al., 2000). A master list of variables, their description, source, and how they were used in the study may be found in Table 4.1.

2.3 Variables from the FIA database

FIA data are used to direct forest policy and programs, as well as to drive numerous ecological analyses across the Nation. To accurately capture the condition of the forests within these plots, multiple attributes are measured at three different scales, represented by Phases (USDA, 2010). Phase II is ground-sampled data measured within multiple permanent fixed-radius plots that are each designed to cover 0.41-ha (1-ac) (Fig. 4.2). Overstory tree and stand attributes are the parameters measured at this level. Phase II data collected from the inventory year 2002, or Cycle 7, was used for this analysis (USDA, 2010).

Inventory foresters annually measure a portion of the Phase II plots (hereafter referred to as "FIA plots"). The data is then organized and entered into several tables within the overall database. The PLOT, COND, TREE, and SITETREE tables contained the information used to conduct this study (USDA, 2010). Data extracted included the location information for the plots, such as the state, county, measurement year, month, and date, as well as the actual geographic coordinates. The species, condition (live, dead, or removed), damage, and tree class code (growing stock, rough cull, rotten cull) was collected for all trees within the plots. Ownership, forest type, condition status (forest, non-forest, water), slope percent, aspect, evidence and type of disturbance, SI, and silvicultural treatment were also extracted for each plot. The SI was estimated from the measured heights of site trees at base age 50. Site index varies with species,

so it was necessary to have the species and age for which the recorded SI value was based (USDA, 2010).

2.4 Standardization of the FIA SI values

The SI values within the FIA database were standardized to three separate sets of SI estimates: white oak (*Quercus alba* L.*)*, yellow-poplar, and upland oak. White oak was chosen because it is ubiquitous throughout the southern Appalachians and it can occur on a wide range of soils (Rogers, 1990). Yellow-poplar is a site demanding species and occurs on deep, well drained soils on good sites (Beck, 1990). Upland oak was used because it has been correlated to the FSQI. Conversion equations were from Doolittle (1958), Olson and Della-Bianca (1959), and Johnson et al. (2005).

2.5 Screening of the FIA database

Screening of the FIA database was done to ensure that the FIA plots used in this analysis were forested and minimally disturbed (Appendix A). The original FIA database for Cycle 7 in North Carolina contained 5908 plots. Of these, 930 occurred in the Blue Ridge physiographic province. Seven hundred and sixty-seven plots were on were forested land. The actual locations of the FIA plots were required in order to accurately relate the environmental characteristics of the site to the point estimates of productivity, so any plots that did not have a recorded location were excluded. Plots with a recorded disturbance code or silvicultural treatment code of any type were removed to ensure the results were not a reflection of disturbance or management. Disturbances were recorded on plots if they covered at least one acre, occurred since last measurement, and caused damage or mortality to 25% of the trees within the plot (USDA, 2005). Further screening provided that the plots be within the six study counties. SSURGO data, which were used in this study to determine available water supply of the soil series in the study area, were not available for Swain County, NC (Soil Survey Staff, NRCS, USDA, 2009). This led to the removal of 15 plots that were in that county. It was discovered that some of the FIA plots had duplicate geographic coordinates for the actual plot locations; these were excluded from the dataset. A final analysis of the tree species within the plots indicated there were high-elevation spruce-fir communities within the database. These were taken out as well.

2.6 Available water supply from the SSURGO database

Whole-profile available water supply was derived for each FIA plot from the mapping unit data in the spatial and tabular databases from the SSURGO database. SSURGO data were obtained for Buncombe, Haywood, Jackson, Madison, and Yancey Counties, NC, as well as the Smoky Mountains (Soil Survey Staff, 2009). Spatial data for Swain County were not available. Available water supply is the total volume of water available to plants at field capacity, or the water that a soil can hold against the force of gravity (Brooks et al., 2003), for the full depth of the soil described. It is a weighted value based on the components within the mapping unit.

2.7 GIS extractions and independent measures of site quality

A 10 m DEM was obtained from the U.S. Geologic Survey National Elevation Dataset (Gesch et al., 2002; Gesch, 2007). Basic surface analyses, including aspect and slope percent were generated from the DEM using ArcGIS 9.3 (Hillier, 2007). Elevation was extracted from the DEM for all plots.

Hydrological characteristics of the area were used to calculate a measure of slope position (summit, shoulder, backslope, toeslope, footslope, and floodplain) from the DEM. Two layers were developed that depicted downhill and uphill flow length between ridges and streams. The two flow length rasters were then used in the following algorithm:

$$\textit{Slope Position} = \textit{Downhill flow length}/(\textit{Uphill flow length} + \textit{Downhill flow length}) \qquad (1)$$

where *Slope Position* is expressed as a percent, *Downhill flow length* is calculated as the longest flow path, in meters, from each cell to a sink or outlet on the edge of a raster, and *Uphill flow length* is calculated as the longest upslope distance, in meters, along the flow path from each cell to the top of the drainage divide (Hillier, 2007). This calculation allowed for an index of slope position as a percent of the slope distance, where 0% slope position represented the bottom of the slope at stream edge and 100% was at the local ridge top. The final slope position was classified into six classes using the quantile option to guide the breaks. By comparing this final grid to the original DEM along with a digital raster graphic of the topographic map, positions on the final grid were classified into the six aforementioned slope positions.

The FSQI was calculated in a GIS by reclassifying the GIS-derived aspect, slope position, and slope (%) grids to reflect the ordinal values (scores) originally assigned by the authors (Table 4.2) (Meiners et al., 1984). The reclassified grids were added to produce a final FSQI grid, which had a value range of 3 to 16. FSQI values were then used to predict upland oak SI values for all plots in this study (Table 4.3) (Meiners et al., 1982).

$$FSQI = AS + SLP + SLPS \tag{2}$$

where *FSQI* is the plot-level Forest Site Quality Index, *AS* is the FSQI score of the measured aspect in degrees, *SLP* is the FSQI score of the measured slope as a percent, and *SLPS* is the FSQI score of the measured or observed slope position.

No standard GIS algorithm has been developed to represent the TSI in a GIS. For this application it was determined, after working with several iterations, that the following algorithm best captured the TSI within the study area:

$$TSI = (P - A) \ / \ R \tag{3}$$

assuming a circular plot with a radius of 75 m, where *TSI* is the Terrain Shape Index, *P* is the elevation of the subject grid cell, *A* is the average elevation of grid cells at a radius *R* from the subject grid cell, and *R* is the radius in distance units, which was 75 m for this purpose. Depending on where the TSI is applied, the range of final values can vary, but they are always distributed around the value 0, which represents a planar slope. The TSI values for each plot were converted to yellow-poplar SI values using the original linear equation from McNab (1989), who was able to explain 51% of the variation between actual yellow-poplar SI and predicted yellow-poplar SI using the TSI:

$$\textit{Yellow-poplar } SI_{50} \ (m) = 53.6 \ (TSI) + 32.9 \tag{4}$$

2.8 Climate data, vapor pressure deficit, and the annual water budget

Climate data from the Daymet database (Thornton et al., 1997; Thornton and Running, 1999; Thornton et al., 2000) are widely used in many types of ecological models. The data are interpolated and extrapolated from daily weather observations, which then are used to model grids of the weather data for the entire United States. One-kilometer resolution files depicting 18-year annual means (1980-1997) were downloaded for mean air temperature (^{O}C), growing degree-days, total annual precipitation (mm), total shortwave radiation (MJ m^{-1} day^{-1}), and average water vapor pressure (kPa). The mean air temperature represents the yearly mean of the average air temperature for a 24-hour period (Thornton et al., 1997), which is further averaged over 18 years. For each plot there was one value for each of the climate parameters extracted, which represented an 18-year mean for that parameter in that location.

Growing degree-days was used as a stand-alone predictor variable. Growing degree-days represent the summation for a year of the daily mean air temperatures for the period that are greater than 0.0 ^{O}C (Thornton et al., 1997). Since we were interested in the biologically relevant relationships to SI based on water availability, the remaining climate data were used as inputs into calculations that depicted the demand for water within the plots.

Vapor pressure deficit was calculated by subtracting actual vapor pressure from the saturated vapor pressure.

$$\textit{Vapor Pressure Deficit (kPa)} = \textit{Saturated VP} - \textit{Actual VP} \qquad (5)$$

Actual vapor pressure was obtained from Daymet. Saturated vapor pressure was calculated from mean air temperature using the following equation provided by Jensen et al. (1990):

$$e_s = 0.6108 \text{ x } \exp\left[17.27 \text{ x } T_{mean} / (T_{mean} + 237.3)\right] \qquad (6)$$

where, e_s = saturated vapor pressure in kPa and T_{mean}= mean air temperature in ^{O}C.

The long-term annual water budget was calculated for each plot by subtracting potential evapotranspiration (PET) from total precipitation.

$$AWB = PPT - PET \tag{7}$$

where *AWB* is the Annual water budget (mm), *PPT* is the 18-year mean annual precipitation (mm), and *PET* is Potential Evapotranspiration (mm). Losses from groundwater seepage (*l*) and changes in soil storage (*Q*) were assumed to be minimal. PET was estimated in place of *ET*. Potential evapotranspiration represents the amount of water loss from an ecosystem through transpiration and evaporation without resistance other than atmospheric demand (Brooks et al., 2003). There are several ways to calculate PET, but the one chosen for this application was based on the Turc method that used mean air temperature and total shortwave radiation, assuming a mean relative humidity of >50% (Lu et al., 2002). This method was chosen because data was available to calculate it, and in a comparison study of six methods of PET, Lu et al. (2002) found that this method resulted in values that were highly correlated with actual evapotranspiration values for watershed scale applications in the southeast US. The Turc PET equation is as follows:

$$PET = 0.013 \text{ x } [T_{mean} / (T_{mean} + 15)] \text{ x } (R_s + 50) \tag{8}$$

where PET = mean potential evapotranspiration (mm day^{-1}); T_{mean} = mean air temperature in ^{O}C; R_s = total shortwave radiation (cal cm^{-2} day^{-1}), and where cal cm^{-2} day^{-1} equals (100/4.1869) MJ m^{-2} day^{-1}. The PET values for each plot were scaled up to a year to get annual estimates. Descriptions of the climate and climate-driven calculated variables may be found in Table 4.1.

2.9 Statistical analyses

2.9.1 The linear regression approach to predicting SI

Significant predictors of WO and YP SI were revealed through stepwise multiple linear regressions at a significance level of 0.05. Outlier analysis and overall model fit were achieved through the examination of the values of the studentized residuals, Cook's D statistic, and the Mallows' Cp statistic. To avoid overfitting the model, Mallows' Cp statistic was used as a

criterion for model selection, as was the variance inflation factor of the predictors. The model with the lowest Mallows' Cp score with significant predictors was chosen. SAS/STAT® Software Version 9.2 was used for all statistical analyses.

2.9.2 The classification approach to predicting site quality classes

Land managers may find site quality classes more useful to manage their forests when SI prediction is questionable. The prediction of site quality classes gives a land manager a starting point where to locate the most suitable areas for timber production. In response to this, a classification approach to estimating site quality was developed.

Each plot was classified into one of four site quality classes, as described by Smith (1994), based on the upland oak FIA-measured SI value (i.e., the classified actual SI) (Table 4.4). Smith developed and described these site classes by typical species, upland oak SI ranges, soils, rotation ages, physical environment, and approximate yields (1994) (Appendix B). For each plot, FSQI-predicted SI was also classified into one of the four Smith site quality classes (i.e., the classified predicted SI) (Tables 4.3 and 4.4). By comparing the classified actual SI values to the classified predicted SI values, percent agreement was calculated by taking the sum of the number of plots that had matching classified values and dividing by the total number of plots (e.g., Table 4.7).

A modification to the FSQI was developed to determine the influence of the annual water budget. The range of values for the annual water budget was divided into five equal classes and assigned a value from 1 (lowest annual water budget class) to 5 (highest annual water budget class) (Table 4.5). For each plot, the value of the annual water budget was classified accordingly and added to the original FSQI value.

$$Modified\ FSQI = FSQI + CAWB \tag{9}$$

where the *Modified FSQI* is a new index number for site quality based on the combined effect of topography and the water budget, *FSQI* is the original FSQI score for a plot, and *CAWB* is the original annual water budget value for a plot classified into one of 5 classes from Table 4.5. The

modified FSQI value was then classified into one of the four Smith site quality classes based on the values from Table 4.4. These values were compared to the classified actual SI for percent agreement. Errors were analyzed for normality.

3. Results

3.1 Descriptive statistics

The final number of plots included in the study was 203. Measured parameters in the plots varied considerably (Table 4.6). Of interest was the fact that none of the plots were predicted by the FSQI to have an upland oak SI greater than 26 m (85 feet tall at 50 years of age), which would be indicated by FSQI values of 15 to 16. Within all plots there was a wide range of water available for tree growth, as indicated by the ranges of the annual water budget and the available water supply. This is a common characteristic within the forests of the southern Appalachians, and one of the reasons it was hypothesized that site quality would be related to the water budget.

3.2 The linear regression approach to predicting SI

3.2.1 The WO SI predictive model

Stepwise multiple linear regression of all predictor variables indicated that WO SI within the 203 plots in the study area was a function of the FSQI and the annual water budget (Fig. 4.3). The multiple linear regression model of WO SI is as follows ($p > 0.0001$):

$$\text{WO SI } (m) = 19.9755 + 0.3310(\text{FSQI}) - 0.0026(\text{Annual Water Budget}) \qquad (10)$$

A general trend of increasing WO SI was seen with increasing FSQI score and decreasing growing season water budget. The R^2 of the final model was 0.13. Variance inflation was less than 1.06 for both predictor variables in the final model, indicating no autocorrelation. No other predictor variables met the significance level of 0.05 to be entered into the model. Mallows' Cp score indicated the best fitted model to be the one shown above.

Standardized residuals ranging from -2.6 to 2.7 (raw residual range of -8.1 m to 9.1 m) for the WO SI model were scattered randomly above and below the zero line. The pattern of the

standardized residuals did not indicate any bias in the predicted values. Additional examination of the histogram of the standardized residuals indicated a normal distribution. Large standard residuals were minimal, as indicated by the tails of the histogram. Examination of the studentized residuals and Cook's D statistic revealed the presence of several outliers; however, when a subset of the data without the outliers was modeled, it only improved the fit by one percent.

3.2.2 The YP SI predictive model

Stepwise multiple linear regression of all predictor variables indicated that YP SI within the 203 plots in the study area was a function of the annual water budget, the FSQI, and the available water supply ($p > 0.0001$).

$$\text{YP SI (m)} = 18.4906 - 0.0034(\text{Annual Water Budget}) + 0.6650(\text{FSQI}) + 0.0206(\text{Available Water Supply}) \quad (11)$$

A general trend of increasing YP SI was seen with decreasing amounts of water in the annual water budget, an increasing FSQI score, and an increasing amount of water in the available water supply from the soil. The R^2 of the final model was 0.11. Variance inflation was less than 1.05 for all predictor variables in the final model, indicating no autocorrelation. No other predictor variables met the significance level of 0.05 to be entered into the model.

Standardized residuals ranging from -3.4 to 2.8 (raw residual range of -23.7 m to 19.42 m) were scattered randomly above and below the zero line. The histogram of the standardized residual values indicated a slight skewing towards the positive standardized residual values, which would indicate that the model may be biased towards underpredicting SI. Examination of the studentized residuals and Cook's D statistic revealed the presence of several outliers; however, when a subset of the data without the outliers was modeled, the model was not improved significantly.

3.3 The classification approach to predicting site quality classes

Percent agreement between the classes of FSQI-predicted SI and the classes of the FIA-measured SI indicated that there was an overall agreement of 27% (Table 4.7). The residuals of this comparison were analyzed and plotted as a histogram (Fig. 4.4). The distribution of the residuals was biased and indicated that the FSQI was underpredicting the actual SI. The residuals on the x-axis depict the range of residuals, and positive numbers indicate underprediction. For example, if the classified actual SI was 4 and the classified predicted SI was 2, then the residual would be 2, indicating that the FSQI was underpredicting the actual SI. The residual value of 0 represents agreement between classes. The pattern of the histogram indicates that the FSQI tended to underpredict by at least one class most often in this scenario.

When the FSQI was modified by the annual water budget to create the Modified FSQI (see Equation 7), the percent agreement between the classes of Modified FSQI-predicted SI and the classes of FIA-measured SI increased by 13%, for a total of 40% agreement (Table 4.8). The distribution of the residuals was examined and it appeared that the modification to the FSQI corrected for the bias in the residuals (Fig. 4.5). Instead of the pattern of underprediction that was previously evident by using only the FSQI, a pattern of increased accuracy was achieved by using the Modified FSQI. This was seen in the overall increase and occurrence of the number of plots with a 0 residual. In other words, the FSQI modified by the annual water budget appeared to predict the actual SI more accurately and more often versus the previous prediction by using the FSQI alone.

A final comparison analyzed the number of plots that were +/- one class. The diagonals directly above and below the bold diagonal numbers in Tables 4.7 and 4.8 were summed for each table and divided by 203. A 50% increase in the number of plots accurately classified was achieved by using the modified FSQI versus the original FSQI to predict actual SI (Table 4.9). An 8% reduction in the number of plots misclassified by +/- 1 class was gained by using the modified FSQI instead of the original FSQI to predict actual SI.

4. Discussion

The predictive models of WO and YP SI produced by linear regression confirmed similar biological relationships that have been reported for decades: that the distribution and productivity of upland hardwood tree species are associated with topography and water (Bolstad et al., 2001; Callaway et al., 1987; Golden, 1981; McNab, 1989; McNab and Loftis, in press; Whittaker, 1956). However, the accuracy of the models was low, which limited their usefulness as a management tool. The observed WO SI values appeared to fit the model, but closer inspection revealed that the coefficients of the predictors, while significant, were small and did not adequately explain the variation in WO SI (Fig. 4.3).

It was interesting to find that both SI models had an inverse, although weak, relationship to the annual water budget. It was hypothesized that a more productive forest will have greater leaf area, and therefore a higher rate of evapotranspiration. An increase in PET relative to the precipitation could cause a smaller annual water budget in a forest with a high SI. However, this idea needs to be tested. On the other hand, one may think site quality should respond positively to this variable. Low values for the available water budget means that there is a high amount of water that is being lost through evapotranspiration, leaving less water in the budget overall. This could be the result of aspect differences, but this should have been accounted for as part of the FSQI in the linear equation. Perhaps if radiation and hillslope shading alone were used to modify the PET, we could get a better estimate of the annual water budget.

There are two issues that may have constrained the explanation of the relationships among the variables in these models: the choice of analysis method and the choice of independent variable. Multiple linear regression is a powerful statistical tool when properly applied. However, many ecological relationships are non-linear, and as a result, linear regression may lead to a large amount of unexplained variance as occurred in this study (Guisan et al., 2002). Recently, Monserud et al. (2006) used multiple linear regression to predict the SI of lodgepole pine (*P. contorta* Douglas ex Louden var *latifolia* Engelm. ex S. Watson*)* at base age 50, as a function of climate in Alberta, Canada. In a forest that met the assumptions of using SI, the model was only able to account for 27% of the variation in lodgepole SI. Iverson et al. (2009) stated that, in 15 years of species modeling, the traditional parametric approaches to

modeling the environment do not adequately capture the complex interactions between and among nonparametric and nonlinear environmental relationships. It does, however, provide a good first cut at discerning important relationships between trees and their environment, and it is easy to use and interpret, unlike some of the more recent nonparametric approaches (Aertsen et al., 2010).

A second issue to consider is SI. Site index has become the standard tool to quantify site quality primarily because of its strong relationship to the growth and yield of forests and its ease of use. It incorporates a direct measure of plant response, which has shown to be effective in predicting site (McNab and Loftis, in press). The main drawback to using site index is that it requires the user to accept a number of underlying assumptions that are either not known or ignored (Beck and Trousdale, 1983). The forests of the study area have been extensively disturbed, and although they are quite resilient, the standing vegetation may or may not represent the inherent site quality. This would lead one to believe that SI underestimates the site quality more often than not, especially in areas with high site quality.

Upon review of the linear regression results, it became clear that the focus of this study may have been too narrow. In other words, if the underlying premise of the study was to develop tools to predict the site quality of upland hardwood forests in the southern Appalachians for management purposes, then the prediction of SI values on small plots of relatively undisturbed land may have been causing us to "not see the forest for the trees." Forests are often described as an assemblage of forest types, or groups of species that commonly occur together, for management purposes (Eyre, 1980). In light of this, the classification approach became more relevant to the goal of developing management tools.

Numerous studies have developed classifications for the upland hardwood forests of the region based on topography and species composition (McNab, 1989; McNab and Loftis, in press; Meiners, 1984; Parker, 1982), and while all of these studies infer a moisture gradient, none incorporate a direct measure of water supply or demand within their schemes. In some of the regions where the classification models were developed, this makes sense. For instance, the FSQI was developed in the Ridge and Valley, where climate is fairly uniform, so topography

was considered the primary influence on the supply of available water for tree growth. However, the mountains of the Blue Ridge are extremely variable with regard to rainfall due to the complex terrain. Asheville, NC, located in the Asheville Basin, receives as little as 900 mm of annual rainfall because it is in a rain shadow created by the surrounding mountains. On the other hand, Coweeta Hydrological Laboratory, less than 100 km from Asheville, can receive over 2000 mm of annual precipitation, one of the highest rates in the eastern United States (USDA, 2006). Incorporating a measure of the supply and demand for water to account for a different climatic regime appeared to increase the predictability of the terrain-based FSQI for use in the Blue Ridge in this analysis. The topographic/water budget classification used here increased accurate classification overall by 50%. It could be improved by further reducing the number of classes off by +/- one, which decreased only by 8% by incorporating the annual water budget. In an attempt to improve this, multiple combinations of assigned values for the classification of the annual water budget were tested and the errors assessed, but none achieved the percent accuracy or a normal distribution of errors like the one presented here.

Another point that sharpened the focus of the study was the choice to incorporate variables that had a direct physiological impact on the growth of the trees. There appears to be a divergence in the literature in the approaches to modeling forest site quality based on environmental variables. Many have and continue to include elevation in predictive models to explain the majority of the variation in the distribution of tree species across the landscape. In fact, elevation was highly correlated to FIA measures of SI in Chapter 2. But elevation is simply a proxy for a temperature and moisture gradient, and there exist few studies (e.g., Allen et al., 1991; Ohmann and Spies, 1998) that have attempted to relate direct resource variables to the groupings of vegetative species. Lookingbill and Urban (2004) found that a mechanistic model using temperature, radiation, and soil moisture as predictors explained more variance within the distribution of forest community types than did proxy variables such as elevation. The findings from the classification analysis in this study suggest that the inclusion of these biologically relevant variables, such as the long-term annual water budget, may increase our power to understand and predict the interaction between trees and the complex environment of the study area.

The second chapter of this dissertation reported that indices of topography and vegetation were significantly correlated to FIA measures of site quality across the Blue Ridge. Further analysis of landscape-forest interactions in the Ridge and Valley revealed that the presence and abundance of site demanding species, especially yellow-poplar, could be used to identify colluvial soils, which are known to be more productive on the sideslopes in southwestern Virginia. And finally, this study suggests that combining a measure of water supply and demand with topography may improve site quality measures compared those based on topography alone. These results, taken as a whole, indicate that the modeling and sequential layering of these data may serve as an effective approach to create tools that will delineate upland hardwood site quality where the SI cannot be used in the forests of the Southern Appalachians.

5. Conclusion

The hypothesized relationships that were posed in the introduction were revealed through this analysis, but accuracy varied according to method. In the study area, site quality was found to be a function of topography, the annual water budget, and the available water supply, but the accuracy of the linear models was low. By incorporating the annual water budget into the FSQI, the classification accuracy of predicted upland oak SI increased by 50%. Refinement of the classification values and validation of the model need to be done to see if this classification could serve as a management tool.

Several modifications to the water budget classification approach may improve its accuracy. First, better climatic data could improve the water budget equation. Long-term monthly data could target the growing season water budget and perhaps yield better results. Also, PET could be modified by radiation and hillslope values to clarify the relationship between SI and the annual water budget.

There is a tremendous amount of data that is available with which to model forest-landscape interactions and site quality. Where no accurate maps of site quality exist, these results indicate that the combination of this extensive database, other publicly available data, and GIS modeling may provide effective management tools to correctly delineate site quality across large areas of the southern Appalachians.

6. Acknowledgements

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Table 4.1. All variables, their description, source, and how they were used in the study.

Variable	Description	Source	How it was used in the study
FIA Plot Variables:			
FIA SI	Original measured site index, base age 50, from the FIA plot, based on various site trees and reported in meters	FIA database	Standardized to separate WO SI, YP SI, and Upland Oak SI values for all plots
Location	State, county, and plot in which the FIA plot was located	FIA database	Used to determine inclusion in the study
Measurement date	Day, month, and year when the FIA plot was measured	FIA database	Used to determine inclusion in the study
Actual geographic coordinates	The actual location of the plot (lat/long) in the Geographic Coordinate System North American Datum 1983	FIA database	Used to extract GIS-derived variables for the plots
Tree species	The species of each tree measured within the FIA plot	FIA database	Used to determine inclusion in the study (in the case of spruce-fir plots)
Tree condition	Described the condition of individual trees measured in the FIA plot; live, dead, or removed	FIA database	Used to determine inclusion in the study
Damage	Described the type and extent of any damage that individual trees within the FIA plot since last measurement	FIA database	Used to describe the plots
Tree class code	Described the individual trees measured in the FIA plot as growing stock, rough cull, or rotten cull	FIA database	Used to describe the plots
Ownership	Described the FIA plot as being on public or private land	FIA database	Used to describe the plots
Forest type	Described the tree species assemblage within the FIA plot	FIA database	Used to describe the plots
Plot condition	Described the FIA plot as being in forest, non-forest, or water	FIA database	Used to determine inclusion in the study
Slope percent	The slope percent of the FIA plot	FIA database	Used to describe the plots
Aspect	The aspect of the FIA plot; azimuth in degrees	FIA database	Used to describe the plots
Disturbance	Described the type and extent of disturbance	FIA database	Used to determine inclusion in the study

Variable (cont.)	**Description** (cont.)	**Source** (cont.)	**How it was used in the study** (cont.)
FIA Plot Variables:			
Silvicultural treatment	Described the type of silvicultural treatment the FIA plot had incurred since the last measurement	FIA database	Used to determine inclusion in the study
Site Tree	Tree species upon which the SI measurement had been based	FIA database	Used to standardize the FIA SI values into WO SI, YP SI, and Upland oak SI
Standardized FIA SI Variables:			
White oak SI	Converted FIA site index standardized to WO SI, base age 50; reported in meters	Converted from FIA SI	Response variable used in linear regression approach to predict SI
Yellow-poplar SI	Converted FIA site index standardized to YP SI, base age 50; reported in meters	Converted from FIA SI	Response variable used in linear regression approach to predict SI
Upland Oak SI	Converted FIA site index standardized to Upland Oak SI, base age 50; reported in meters	Converted from FIA SI	Classified into one of four Smith site quality classes for use in the classification approach to predict site quality classes
SSURGO data:			
Available water supply	The weighted average of the available water supply for the whole profile of a mapping unit; reported in mm	SSURGO	Predictor variable used in linear regression approach to predict SI
GIS Extractions:			
Aspect	GIS derived landscape variable; the direction of a slope face; azimuth in degrees	10 m DEM	Used in the calculation of the FSQI
Slope	GIS derived landscape variable; rise/run; reported in %	10 m DEM	Used in the calculation of the FSQI
Slope position	GIS derived landscape variable; position on the profile of a slope (ridge, shoulder, sideslope, footslope, toeslope, and bottom; reported as percent	GIS algorithm calculated from a 10 m DEM	Used in the calculation of the FSQI
Elevation	GIS derived landscape variable; reported in meters	10 m DEM	Used to describe the plots

Variable (cont.)	**Description** (cont.)	**Source** (cont.)	**How it was used in the study** (cont.)
GIS Extractions:			
FSQI	The Forest Site Quality Index (Meiners et al., 1984); predictor of up oak SI based on aspect, slope % & slope position	GIS algorithm	Predictor variable used in linear regression approach to predict SI; also used in classification approach
TSI	The Terrain Shape Index (McNab, 1989); index of the shape of a landform within a plot	GIS algorithm	Predictor variable used in linear regression approach to predict SI
Daymet Climate and Climate-driven Variables:			
Mean air temperature	The yearly mean of the average air temperature from a 24-hour period, averaged for 18 years (1980-1997); reported in ^{O}C	Daymet	Used in the calculations of potential evapotranspiration and saturated vapor pressure
Growing degree days	The annual summation of the mean air temperatures for the period that are greater than $0.0^{O}C$, averaged for 18 years (1980-1997)	Daymet	Predictor variable used in linear regression approach to predict SI
Total annual precipitaton	The total accumulated precipitation over a year, averaged for 18 years (1980-1997); reported in mm	Daymet	Used in the calculation of the annual water budget
Total shortwave radiation	The yearly mean of the total daily incident shortwave radiation flux, averaged for 18 years (1980-1997); reported in MJ m^{-1}	Daymet	Used in the calculation of potential evapotranspiration
Mean water vapor pressure	The yearly mean of the average partial pressure of water vapor in the air near the surface; reported in kPa	Daymet	Used in the calculation of the vapor pressure deficit
Saturated vapor pressure	Determined by air temperature, the partial pressure of water vapor in a saturated atmosphere (Jensen et al., 1990); reported in kPa	Calculated	Used in the calculation of the vapor pressure deficit
Vapor pressure deficit	The difference between the saturated vapor pressure and the mean water vapor pressure; reported in kPa	Calculated	Predictor variable used in linear regression approach to predict SI
PET	Potential evapotranspiration; water loss (mm) from an ecosystem through transpiration and evaporation without resistance other than atmospheric demand; based on Turc	Calculated and scaled up to an annual measure	Used in the calculation of the annual water budget; also used separately as a predictor variable in the linear regression approach to predict SI

Variable (cont.)	**Description** (cont.)	**Source** (cont.)	**How it was used in the study** (cont.)
Daymet Climate and Climate-driven Variables:			
Annual water budget	The difference between total annual precipitation and total annual PET; assumes groundwater seepage and changes in the available water supply are minimal (Brooks et al., 2003); reported in mm	Calculated	Predictor variable used in linear regression approach to predict SI; also classified and used in the classification approach to predict site quality classes
Classified Variables used in the Classification Approach:			
Smiths classes of Upland Oak SI	Upland Oak SI classified into one of four site quality classes described by Smith (1994), see Appendix B	Upland Oak SI	Actual measure of SI used in classification approach to predict site quality classes; also referred to within the text as 'classified actual'
Smiths classes of the original FSQI	Original FSQI values classified into one of four site quality classes described by Smith (1994), see Appendix B	FSQI	Predicted measure of SI used in classification approach to predict site quality classes; also referred to in the text as 'classified predicted'
Smiths classes of the modified FSQI	Original FSQI values plus the classified annual water budget value classified into one of four site quality classes described by Smith (1994), see Appendix B	FSQI and the annual water budget	Predicted measure of SI used in classification approach to predict site quality classes; also referred to in the text as 'classified new predicted'
Classified annual water budget	The range of the values of the annual water budget divided into five equal classes and classified into 1 of 5 values	Annual water budget	Used to improve the prediction of site quality classes in the classification approach

Table 4.2. Ordinal values assigned to variables in the FSQI model (after Meiners et al., 1984).

FSQI Value	Aspect	% Slope	Slope Position
1	196-260	>=60	Shoulder
2	166-195; 261-280	45 – 59	Backslope
3	146-165; 281-340	30 – 44	Summit
4	0-20; 341-360	15 – 29	Footslope
5	81-145	0 – 14	Toe Terrace Floodplain
6	21-80		

Table 4.3. Predicted upland oak SI values that correspond to the FSQI index values (after Meiners et al., 1984).

FSQI Value	Upland Oak SI_{50} *(m)*	FSQI Value	Upland Oak SI_{50} *(m)*
3	14	10	21
4	15	11	22
5	16	12	23
6	17	13	24
7	18	14	25
8	19	15	26
9	20	16	27

Table 4.4. Classified values for FIA-measured SI and FSQI ranges of site quality.

Value*	FIA Upland Oak SI_{50} Ranges, *m* (*ft*)	FSQI Value Ranges
1	<= 17 (55)	3 – 6
2	17 – 21 (56 – 70)	7 – 10
3	22 – 26 (71 – 85)	11 – 14
4	>= 27 (86)	15 - 16

*based on classification by Smith, 1994; see Appendix B for additional characteristics of the site classes.

Table 4.5. Classified values of equal ranges of the annual water budget (Long-term mean annual precipitation minus long-term mean annual PET).

Value	Annual water budget Range (*mm* yr^{-1})
1	0 – 281.03
2	281.04 – 562.06
3	562.07 – 843.09
4	843.10 – 1124.12
5	1124.13 – 1405.15

Table 4.6. Descriptive statistics of the 203 FIA plots included in the study.

Variable	Mean	S.D.	Min	Max
White oak SI (base age 50, m)	21	4	12	33
Yellow-poplar SI (base age 50, m)	25	7	6	45
Upland oak SI (base age 50, m)	23	4	14	36
FIA Slope (degrees)	44	18	1	90
Aspect (degrees)	176	105	1	364
Elevation (m)	1002	250	510	1704
FSQI	9	3	3	14
TSI	0.00	0.12	-0.35	0.33
*Total annual precipitation (mm)**	1547	301	1050	3300
*Daily average air temperature (^{O}C)**	11	1	7	13
Annual mean VPD (kPa)*	0.34	0.04	0.20	0.42
Annual mean PET (mm)*	819	58	650	914
Annual water budget (mm)*	729	337	141	1628
Available water supply (mm)	159	56	0	280

*Calculated or derived from 18-year mean climate data.

Table 4.7. Contingency table depicting percent agreement (4 + 20 + 30 + 0) / 203 = 27%) for the comparison between classes of FIA-measured SI (top row) and classes of FSQI-predicted SI (left column).

Based on count of plot	**Smiths Site Quality Class based on FIA-measured SI**				
Smith Site Quality Class based on FSQI	***1***	***2***	***3***	***4***	**Grand Total**
1	**4**	14	14	5	37
2	12	**20**	52	27	111
3	0	11	**30**	14	55
4	0	0	0	**0**	0
Grand Total					**203**

*+/- 1 class off = 14 + 52 + 14 + 12 + 11 = 103 plots

Table 4.8. Contingency table depicting percent agreement (0 + 16 + 57 + 8) / 203 = 40%) for comparison between classes of FIA-measured SI (top row) and classes of the Modified FSQI-predicted SI (left column).

Based on count of plot	**Smiths Site Quality Class based on FIA-measured SI**				
Smith Site Quality Class based on Modified FSQI	***1***	***2***	***3***	***4***	**Grand Total**
1	**0**	1	1	0	2
2	7	**16**	20	11	54
3	8	22	**57**	27	114
4	1	6	18	**8**	33
Grand Total					**203**

*+/- 1 class off = 1 + 20 + 27 + 7 + 22 + 18 = 95 plots

Table 4.9. Comparison of the number of plots classified accurately, and off by +1 and -1 classes between the original classification based on the FSQI alone and the new classification based on the Modified FSQI (with the annual water budget added).

	Predicted by the FSQI alone	**Predicted by the Modified FSQI**	
	Number of Plots	***Number of Plots***	***Percent Change***
Accurately Classified	54	81	+50%
Off by + 1 and -1	103	95	-8%

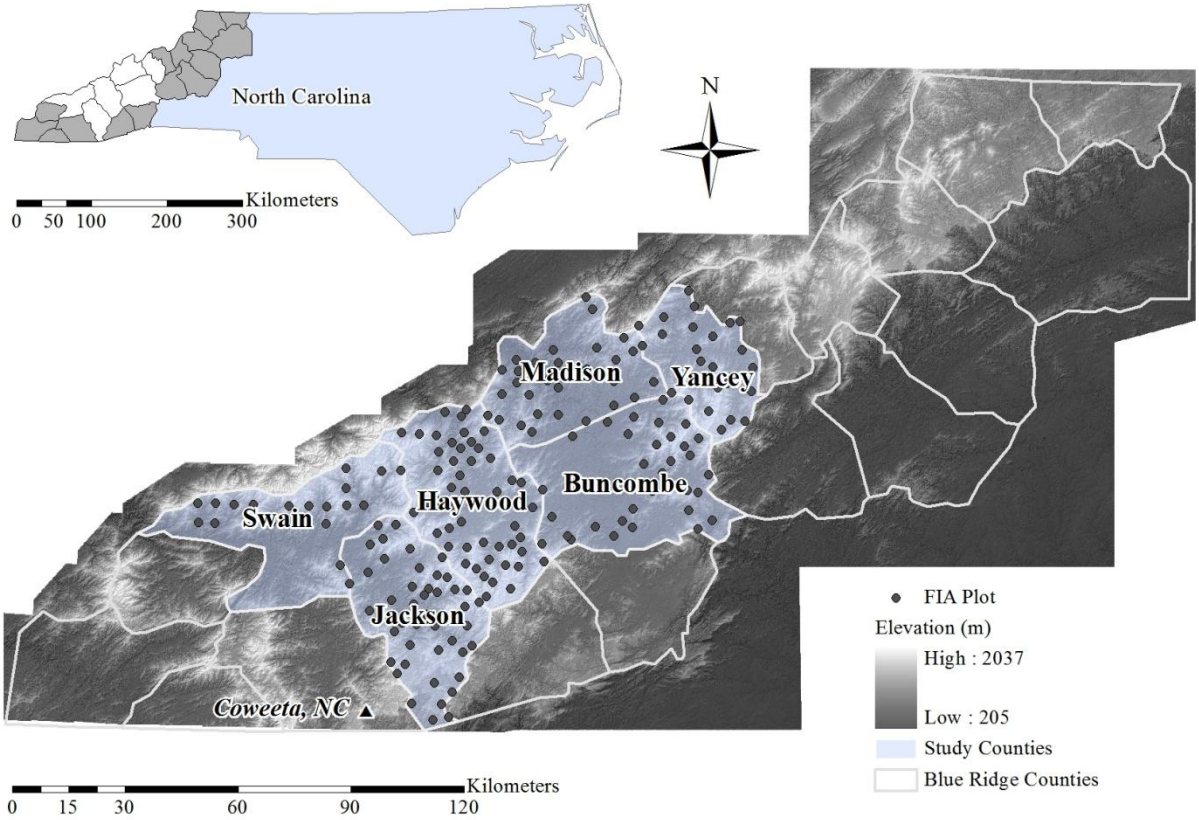

Fig. 4.1. Study area and approximate locations of FIA plots within the Blue Ridge Mountains of western North Carolina.

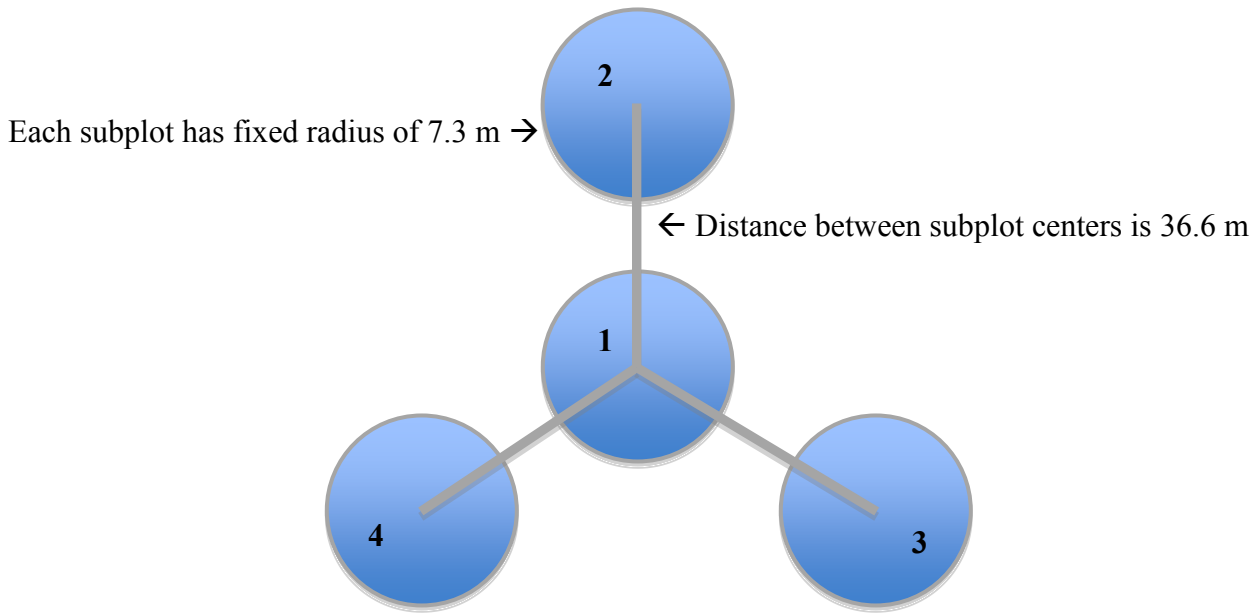

Fig. 4.2. Example of an FIA mapped plot design (after USDA, 2010). The plot is composed of 4 subplots, each with a fixed radius of 7.3 m, in which the Phase II data is collected. Distance between the subplot centers is 36.6 m horizontal distance. The azimuth between the center of subplot 1 and 2 is 360°, between 1 and 3 is 120°, and between 1 and 4 is 240°.

FIA WO SI_{50}=19.9755+0.3310(FSQI)-0.0026(Annual Water Budget)
R^2=0.13, p<0.0001, $s.e.$=3.38 m

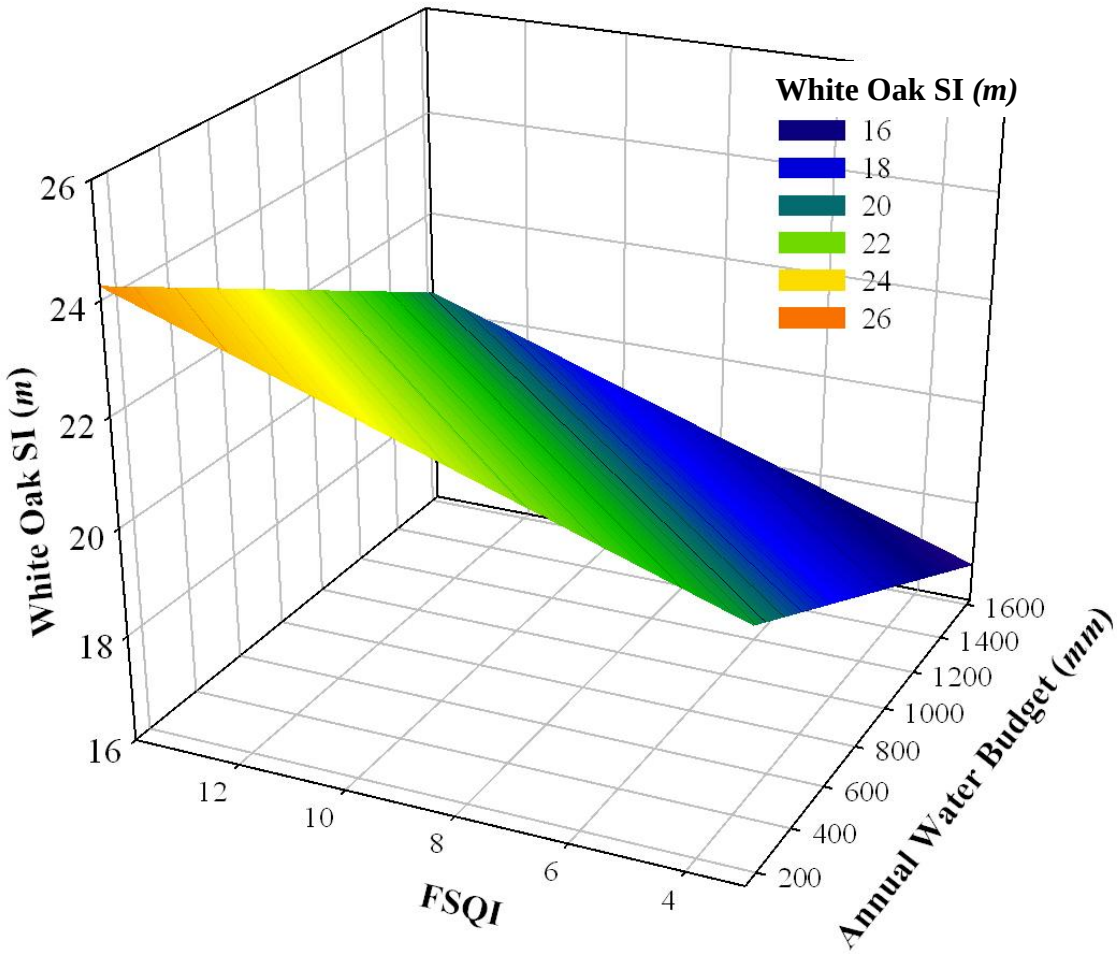

Fig. 4.3. The linear model of WO SI_{50} as a function of the FSQI and the Annual Water Budget (n=203).

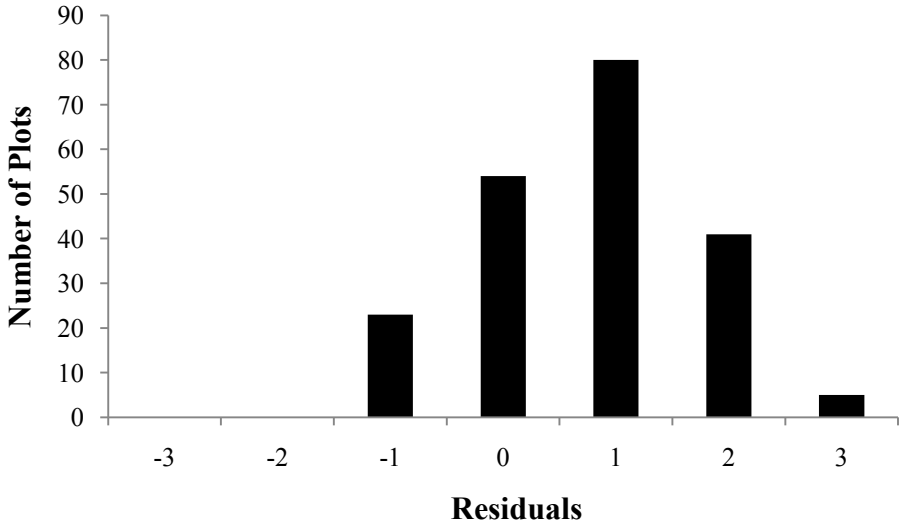

Fig. 4.4. Histogram of the residuals between classes of FIA-measured SI and classes of FSQI-predicted SI (*n*=203).

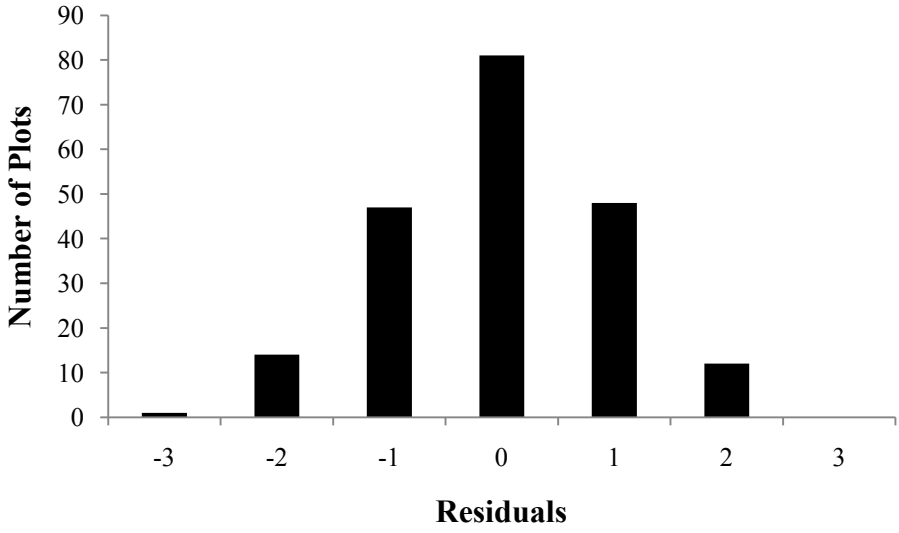

Fig. 4.5. Histogram of the residuals between classes of FIA-measured SI and classes of Modified FSQI-predicted SI (*n*=203).

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Chapter 5

Improving Site Quality Estimates in the Upland Hardwood Forests of the Southern Appalachians with Environmental and Spatial Modeling: Conclusions from Three Studies

1. Study Summaries

First Study:

Predicting Upland Hardwood Site Quality in the Southern Appalachians using FIA Data and Geospatial Modeling

Within Forest Inventory and Analysis (FIA) plots in a six-county area of the Blue Ridge in western North Carolina:

1. Are FIA measures of forest site quality related to one another?
2. Are FIA measures of forest site quality related to FIA-measured landscape parameters?
3. Do independent indices of forest site quality, based on topography and soil attributes, relate to FIA measures of forest site quality?

Forest Inventory and Analysis (FIA) measures of forest productivity were related to one another, but some relationships were stronger than others. Correlation analysis performed on FIA measures of forest productivity [white oak site index (WO SI), yellow-poplar site index (YP SI), standing basal area, standing volume, and site productivity] revealed that all pair-wise relationships were significant to some degree (Table 2.6). The correlations between FIA site productivity and WO SI and YP SI were the highest among the FIA measures of productivity (ρ = -0.58 and -0.77, respectively). The inverse relationship was a result of the ordination of the FIA site productivity code, which assigns the lowest number to the highest potential productivity. FIA standing basal area and FIA standing volume had the lowest correlations to the other measures, but they were correlated to each other, which would be expected since they are both diameter-based.

FIA measured landscape parameters were not related to FIA measures of productivity, despite the numerous relationships that have been established in the literature. These results suggest that FIA landscape data may not be precise enough for this level of investigation. For example, the FIA Database Description and Users Guide lists and describes sixteen different physiographic class codes, of which nine could potentially be found within the study area (USDA, 2010). However, for the 203 plots in this study, only four physiographic class codes were assigned, and of those four, one class contained 65% of the plots (Fig. 2.3).

Independent measures of forest productivity, based on topography and vegetation, were related to FIA measures of forest productivity. All independent measures of forest productivity were significantly correlated to WO SI, and the strongest correlations were to the Moisture Regime Index (MRI) and the Forest Site Quality Index (FSQI) (ρ = 0.21 and 0.27, respectively) (Figs. 2.4 and 2.5, Table 2.7). Both of these indices also had the strongest correlations to YP SI (Figs. 2.6 and 2.7) among the four indices. The highest correlation seen in Table 2.7 was between YP SI and the MRI (ρ = 0.38). The MRI was the only independent measure of forest productivity correlated to FIA standing basal area, and none of the independent measures of forest productivity correlated to FIA standing volume. All of the independent measures of forest productivity were correlated to FIA site productivity, and the MRI (ρ = -0.23), the FSQI (ρ = -0.29), and the TSI (ρ = 0.20) had coefficients equal to or over 0.20.

These results, taken as a whole, suggest that where accurate measures of site quality do not exist or cannot be measured directly, there may be two alternatives. If a tree inventory is available the MRI can predict site quality based on species composition. A second, and perhaps more efficient approach may be to delineate site quality by modeling the FSQI with a 10 digital elevation model (DEM), which is from a database available for public use. This latter method could give a land manager a first approximation about where to focus his efforts, and additional layers of information, such as precipitation or soil storage, may improve the predictions. The GIS approach used in this study provides the ability to map all forests in SI classes for management planning. The results of this study also indicated that FIA data can be used as the measured variable in the predictive modeling of site quality. FIA measures of productivity,

especially SI and site productivity, can be used in this type of investigation, which may eventually serve to increase the efficiency with which we manage our forests.

<u>Second Study</u>:

Identifying Colluvial Soils in the Ridge and Valley to Refine Measures of Upland Hardwood Site Quality in the Southern Appalachians

On the sideslopes of mountains in the central Ridge and Valley in southwestern Virginia:

1. Can vegetation and topography be used as indicators of colluvial soils and deposits?
2. Can colluvial soils and deposits be predicted according to their topographic signature with a slope change algorithm using a Digital Elevation Model?

On the side slopes within a four-county area of the central Ridge and Valley in southwestern Virginia, topography and vegetation can be used as indicators of colluvial soils. Logistic regression of the predictor variables against the presence or absence of colluvium suggested that colluvium was a function of three covariates: the yellow-poplar basal area importance value (hereafter referred to as yellow-poplar BA), the MRI, and the Terrain Shape Index (TSI) (Table 3.7). As seen in Fig. 3.5a, as the amount of yellow-poplar BA increased in proportion to the total basal area within a plot, so did the probability of being on colluvium. The results seen in Fig. 3.6 were striking. It was clear that yellow-poplar (*Liriodendron tulipifera* L.) was much more abundant on the colluvial soils than the residual soils. Yellow-poplar is not normally found on side slopes unless the soils are sufficiently deep. These findings suggest that the yellow-poplar found on the colluvial plots on side slopes in the study may indicate deeper soils that contribute to higher site quality. The positive relationship depicted in Fig. 3.5b indicated that high MRI scores were associated with an increased probability of being on colluvium. Significant differences were found in mean MRI values between the colluvial and residual plots (Table 3.6). The increased depth and increased water holding capacity of the colluvium on the side slopes tended to support a species assemblage that was more moisture demanding, according to the MRI values. The TSI also predicted the presence of colluvium on side slopes within the study area. This model did not fit the data as well as the MRI or yellow-

poplar BA. It could serve as a relatively simple starting point for the delineation of forest site quality on side slopes through GIS modeling, should no other data, such as an inventory, be available.

Using the methods described within this study, colluvial soils cannot be predicted according to their topographic signature with the slope change algorithm using a DEM. Spearman's rank sum correlation test on the colluvial plots (n=51) indicated no significant correlations between the predicted slope difference values and the field-measured slope difference values. Within the colluvial plots, the 11 x 11 cell neighborhood (110 x 110 m on the landscape) had the highest correlation to field-measured slope difference (ρ=0.14), but it was not significant. T-tests revealed no significant differences in predicted slope difference means between colluvial and residual plots. Even though the field-measured slope difference did not correlate to the predicted slope difference within the plots, there was evidence that colluvial soils on sideslopes as a group did indeed experience a greater slope difference than the residual soils. Zonal statistics indicated that within the colluvial soil polygons on side slopes, the mean predicted slope difference on side slopes increased with an increase in the size of the neighborhood being analyzed. Residual soils showed no such increase, but rather stayed static as the neighborhood size increased (Table 3.13).

The results of this study present an opportunity to identify colluvial soils using vegetation and topography where accurate soils maps do not exist. If a tree inventory is available or a land manager has the time to go to the field, then the MRI or the abundance of yellow-poplar may be useful in delineating areas of colluvial soils and potentially, areas of higher site quality on side slopes in the study area. If no other data is available, a DEM may be modeled for the TSI to give a first approximation for areas of higher site quality based on topography.

<u>Third Study</u>:

Predicting Upland Hardwood Site Quality in the Southern Appalachians as a Function of the Inputs, Supply, and Usage of Available Water

Within Forest Inventory and Analysis (FIA) plots in a six-county area of the Blue

Ridge in western North Carolina:

1. Can FIA measures of SI be predicted by the inputs, supply, and usage of available water?
2. Are site quality classes related to topography and the annual water budget?

Within 203 FIA plots in the six-county study area in the Blue Ridge of North Carolina, FIA measures of SI were predicted by the inputs, supply, and usage of available water. The predictive models of WO and YP SI produced by stepwise linear regression confirmed similar biological relationships that have been reported for decades: that the productivity and distribution of upland hardwood tree species are associated with topography and water (Bolstad et al., 2001; Callaway et al., 1987; Golden, 1981; McNab, 1989; McNab and Loftis, in press; Whittaker, 1956). However, the accuracy of the models was low, which limited their usefulness as a management tool (YP SI R^2= 0.11, WO SI R^2= 0.13).

We had better results from a classification approach. We found that quality classes were related to topography and the annual water budget. When the FSQI was modified by the annual water budget, the percent agreement between actual SI and predicted SI increased by 14%, for a total of 40% agreement (Table 4.8). A 50% increase in the number of plots accurately classified was achieved by modifying the FSQI with a measure of the supply and demand of water within the plots (Table 4.9). An 8% reduction in the number of plots misclassified by +/- 1 class was gained by using the modified FSQI instead of the original FSQI to predict actual SI.

The hypothesized relationships that were posed in the introduction to this study were found in this analysis, but accuracy varied according to method. In the study area, site quality was a function of topography and the annual water budget, and the classification method appeared to be more useful than the linear regression method. The prediction of site quality classes may be more applicable and useful when managing upland hardwood forests where the use of SI may be questionable. Where accurate maps of site quality do not exist, these results suggest that site quality may be predicted by the FSQI and the available water budget.

2. Future Research

The conclusions from these three studies pose several more questions that could be analyzed to refine this research. First, to identify colluvium more accurately in the Ridge and Valley, the MRI values of yellow-poplar could be increased to emphasize its strength as an indicator. Also, the use of remote sensing may hold promise in delineating colluvium in the Ridge and Valley. If imagery could be obtained that would show the spectral signature of yellow-poplar leaf out in the spring, the colluvium may be more accurately mapped. Several modifications to the water budget classification approach may improve its accuracy. First, better climatic data could improve the water budget equation. Long-term monthly data could target the growing season water budget and perhaps yield better results. Also, PET could be modified by radiation and hillslope values to clarify the relationship between SI and the annual water budget.

3. Relevance and Application

The application of the results within this dissertation is management-driven. Site index is unreliable for use in most of the upland hardwood forests of the Southern Appalachians due to disturbance, so we need other metrics that will allow for accurate measures of site quality. Here there exists opportunity to identify and partition the land into more accurate classes of site quality than what is commonly mapped and available.

Smith (1994) categorized the upland hardwood forests of the southern Appalachians into four classes (Appendix B). The first class, Scarlet Oak/White Oak is often found on xeric sites, and as a result, yields are low and timber quality is poor. Soils are thin and rocky, and overall, this type of site is not worth managing for timber production. On the other hand, the fourth class, Yellow-poplar/Mixed Hardwood, is the very best site quality that can be achieved in the southern Appalachians. These sites have deep soils, abundant water and nutrient availability, and result in high quality sawtimber and veneer. There are few limitations for tree growth, and silviculture inputs should produce a high return on investment. These two types of sites are not hard to recognize by a forester, neither are they hard to identify on the landscape, as they both occupy well defined landscape positions. However, the types of forests that are most common throughout the southern Appalachians are those found in classes 2, the White Oak/Black Oak class, and 3, the Red Oak/Sugar Maple class. There can be much overlap between these two

types of forest, and it can be difficult to distinguish between the two. It is within these types of sites that the management tools described in this dissertation could have the most potential.

Because of high grading, disturbance has greatly affected the forests of the southern Appalachians. So potentially, a stand could be composed of mostly poor quality white oak (*Quercus alba* L.*),* black oak *(Q. velutina* Lam.), and chestnut oak (*Q. prinus* L.*),* with an occasional yellow-poplar*,* and be considered subxeric because of the prevalence of oak; when in fact, the site could support a stand with a higher proportion of more valuable species such as northern red oak and yellow-poplar. This would be a missed investment on behalf of the landowner if the proper management tools were not available to correctly quantify the site. The MRI and the FSQI, modified by the annual water budget, could be very effective and easy to use for such a purpose. In many cases, money spent on silvicultural inputs on submesic to mesic sites (i.e., high quality sites) is worth the investment, and by using these tools a landowner could apply site-specific management to increase the return on that investment.

On a larger scale, there is a tremendous amount of data that is available with which to model forest-landscape interactions and site quality. The FIA database is a source of data that could be used for this purpose. We had the unique opportunity to access FIA data and the actual plot locations for this study. Where no accurate maps of site quality exist, the results of this dissertation indicate that the combination of this extensive database, other publicly available data, and GIS modeling can provide effective management tools to correctly delineate site quality across large areas of the southern Appalachians.

Appendix A: Screening Criteria for FIA Plots

Table A.1. Screening criteria applied to Cycle 7 FIA data to determine final sample plots for studies described in Chapters 2 and 4.

Criteria	# Plots after Screen	# Plots Removed
North Carolina Cycle 7	5908	
Outside of the Blue Ridge	930	4978
Not on forested land	767	163
No coordinates available	741	26
Disturbed since last measure	659	82
Received silvicultural treatment	618	41
Outside of the 6-county study area	236	382
FIA duplicate coordinates	223	13
Outside of the SSURGO spatial extent	208	15
Not in upland hardwoods (spruce-fir)	203	5
Final plot totals	**203**	**5705**

Appendix B: Smith's Site Classes

Table B.1. Description of each of Smith's site classes used for the classification of 203 FIA plots in Chapters 2 and 4.

Site Type	Classification Value	Upland Oak SI_{50} (*m*)	Yield ($m\ ha^{-1}\ yr^{-1}$)	Typical Species	Soil Characteristics	Physical Environment
Chestnut and Scarlet Oak (Xeric)						
	1	<= 17	0.19	Chestnut Oak Scarlet Oak Pitch Pine Virginia Pine	Shallow Sandy Acid Residual Inceptisols Entisols	Poorest sites Steep slopes Low fertility and water Ridges and warm aspects Marginal Good for non-timber uses
White and Black Oak (Subxeric)						
	2	17 – 21	0.44	White Oak Black Oak Chestnut Oak Scarlet Oak Pignut Hickory Red Maple	Droughty Some clay Acid Residual Inceptisols Ultisols	Fair to medium sites Upper slopes/ridges on N and E apects Mid/low slopes on S & W aspects Moister than Class 1 Similar to Braun's Oak Chestnut type
Red Oak and Sugar Maple (Submesic)						
	3	22 – 26	0.64	Northern Red Oak Yellow-poplar Sugar Maple Black Cherry White Ash Am. Basswood American Beech	Deep High organic matter Well-drained Colluvial Ultisols Alfisols	Generally cool aspects and positions Mid/upper slopes in coves Good moisture throughout the growing season Similar to Braun's Mixed Mesophytic Very important commercially for growth rates and species
Yellow-poplar and Mixed Hardwoods (Mesic)						
	4	>= 27	1.58	Same as Class 3	Same as Class 3	Very best sites/Coves/High water and fertility At SI=24 then YP is = in competitiveness At SI<24 YP competitiveness decreases At SI>24 YP outcompetes all other species Rapid growth rate and excellent timber quality Few limitations for tree growth Not common and usually small sites

Appendix C: MRI Values for Individual Species

Table C.1. Arborescent species present on plots for the studies within Chapters 2 and 3, and the moisture weight assigned to each species that was used to calculate the plot-level Moisture Regime Index (from McNab and Loftis, in press and other unpublished data). For moisture weights that were not in the original publication, H. McNab concurred with the suggested values through personal communication.

Common name	Scientific name	Moisture Weight
Table mountain pine	*Pinus pungens* Lamb.	1.0
Virginia pine	*Pinus virginiana* Mill.	1.0
Post oak	*Quercus stellata* Wangenh.	1.0
Pitch pine	*Pinus rigida* Mill.	1.5
Scarlet oak	*Quercus coccinea* Muenchh.	1.5
Carolina hemlock	*Tsuga caroliniana* Engelm.	1.5
Downy serviceberry	*Amelanchier arborea* (Michx. f.) Fern.	2.0
Pignut hickory	*Carya glabra* (Mill.) Sweet	2.0
American chestnut	*Castanea dentata* (Marsh.) Borkh.	2.0
Allegheny chinquapin	*Castanea pumila* (L.) Mill.	2.0
Common hackberry	*Celtis occidentalis* L.	2.0
Hawthorne spp.	*Craetegus* spp. L.	2.0
Common persimmon	*Diospyros virginiana* L.	2.0
Eastern red cedar	*Juniperus virginiana* L.	2.0
Apple	*Malus* spp. Mill.	2.0
Blackgum	*Nyssa sylvatica* Marsh.	2.0
Sourwood	*Oxydendrum arboreum* (L.) DC.	2.0
Shortleaf pine	*Pinus echinata* Mill.	2.0
Eastern white pine	*Pinus strobus* L.	2.0
Pin cherry	*Prunus pensylvanica* L. f.	2.0
Southern red oak	*Quercus falcata* Michx.	2.0
Chestnut oak	*Quercus prinus* L.	2.0
Black oak	*Quercus velutina* Lam.	2.0
Sassafras	*Sassafras albidum* (Nutt.) Nees	2.0
Winged elm	*Ulmus alata* Michx.	2.0
Red maple	*Acer rubrum* L.	2.5
Mockernut hickory	*Carya tomentosa* (L.) Nutt.	2.5
Eastern redbud	*Cercis canadensis* L.	2.5
American holly	*Ilex opaca* Aiton	2.5
Sweetgum	*Liquidambar styraciflua* L.	2.5
Loblolly pine	*Pinus taeda* L.	2.5
White oak	*Quercus alba* L.	2.5
Striped maple	*Acer pensylvanicum* L.	3.0
Flowering dogwood	*Cornus florida* L.	3.0
American beech	*Fagus grandifolia* Ehrh.	3.0
Frasier magnolia	*Magnolia fraseri* Walter	3.0
Red mulberry	*Morus rubra* L.	3.0

Common name (cont.)	**Scientific name** (cont.)	**Moisture Weight** (cont.)
Northern red oak	*Quercus rubra* L.	3.0
Black locust	*Robinia pseudoacacia* L.	3.0
American elm	*Ulmus americana* L.	3.0
Slippery elm	*Ulmus rubra* Muhl.	3.0
Sugar maple	*Acer saccharum* Marsh.	3.5
Mountain maple	*Acer spicatum* Lam.	3.5
Sweet birch	*Betula lenta* L.	3.5
American hornbeam	*Carpinus caroliniana* Walt.	3.5
Shagbark hickory	*Carya ovalis* (Wangenh.) Sarg.	3.5
Silverbell spp.	*Halesia* spp. Ellis ex. L.	3.5
Yellow-poplar	*Liriodendron tulipifera* L.	3.5
Cucumbertree	*Magnolia acuminata* (L.) L.	3.5
Bigleaf magnolia	*Magnolia macrophylla* Michx.	3.5
Eastern hophornbeam	*Ostrya virginiana* (Mill.) K. Koch	3.5
Black cherry	*Prunus serotina* Ehrh.	3.5
Eastern hemlock	*Tsuga canadensis* (L.) Carriere	3.5
Silver maple	*Acer saccharinum* L.	4.0
Yellow buckeye	*Aesculus flava* Aiton	4.0
Yellow birch	*Betula alleghaniensis* Britton	4.0
Bitternut hickory	*Carya cordiformis* (Wangenh.) K. Koch	4.0
White ash	*Fraxinus americana* L.	4.0
Green ash	*Fraxinus pennsylvanica* Marsh.	4.0
Black walnut	*Juglans nigra* L.	4.0
American sycamore	*Platanus occidentalis* L.	4.0
Willow spp.	*Salix* spp. L.	4.0
American basswood	*Tilia americana* L.	4.0
Carolina basswood	*Tilia caroliniana* L.	4.0
White basswood	*Tilia heterophylla* L.	4.0