Mapping Upland Hardwood Site Quality and Productivity with GIS and FIA in the Blue Ridge of North Carolina

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Abstract: *The forested ecosystems of the southern Appalachians are some of the most diverse in North America due to the variability in climate, soils, and geologic parent material coupled with the complex topography found throughout the region. These same characteristics cause stands of upland hardwoods to be extremely variable with regard to site quality and productivity. Site index has been the tool most commonly used to measure existing site quality and productivity, but measured site index may not accurately quantify potential site quality and productivity, largely due to ubiquitous disturbance and variable land-use history. Because of this, environmental factors may hold merit in predicting the quality of a forested site in the southern Appalachians. To assess the accuracy of existing methods, three indices developed within the region were used to predict the site quality of the upland hardwood forests throughout a six-county study area in the Blue Ridge physiographic province of western North Carolina. We hypothesized that predictions of site quality generated by the indices would correlate with similar estimates from Forest Inventory and Analysis (FIA) plots. We also predicted that the indices that included multiple types of information would produce higher correlations with FIA estimates. Finally, we felt we would be able to reasonably predict site index, but not basal area or volume increment. The environment of the study area was derived from a layered GIS that depicted variables related to water availability. FIA data and actual plot locations were compared to the predictions. Results indicated a moderate correlation between one index and site quality. The index with multiple layers of information did not produce a higher correlation, and there was no relationship among any of the indices to basal area or volume increment. Future research will include finer-scaled estimates of soil information and estimates of water inputs as well as usage.*

Keywords: Upland hardwood forests, site quality, site productivity, GIS, Blue Ridge.

Introduction

Quantifying site quality and upland hardwood productivity is a major challenge for accurate growth and yield modeling in the upland hardwood forests of the southern Appalachians. These ecosystems are some of the most complex

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In: McWilliams, Will; Moisen, Gretchen; Czaplewski, Ray, comps. 2009. 2008 Forest Inventory and Analysis (FIA) Symposium; October 21-23, 2008: Park City, UT. Proc. RMRS-P-56CD. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. 1 CD.

and diverse in North America due to the many combinations of topography, geology, climate, and landform found throughout the region. These attributes lead to a wide range of site quality and productive capacity from the stand to the region, driven largely by topographic controls on water availability. Site index (Frothingham 1917) has been the standard for measuring site quality and productivity, but accuracy is affected by disturbance, variable land-use history, the presence of suitable trees to measure, and measurement error.

Traditionally, site classification has addressed the landscape by analyzing the vegetation, measuring site index, and inferring relationships of water and nutrient availability based on the current vegetation. However, due to problems with site index accuracy, this methodology often does not capture the true site quality and consequently, estimates of stand growth and yield may be inaccurate. A more precise approach would be to identify the primary environmental variables found to significantly influence the availability of water and nutrients in upland hardwood forests, determine how the variables influence the measured site quality, and then use these relationships to develop a model to predict the quality and productivity of a site.

Site quality is assumed here to be a measure of potential productivity. Site, in silviculture terms, can be expressed qualitatively through the local climate, soil, and vegetation present, and quantitatively through the local productivity, or potential wood production per unit land area per unit of time (Helms 1998; Johnson et al. 2002). Site quality and productivity can be predicted with reasonable accuracy in small areas using measured site index, but the prediction is costly and requires specific vegetation to be present. Field-measured site index is not feasible for use across the entire southern Appalachians. However, previous research has shown that site quality can be interpreted through topographic, edaphic, geologic, and vegetative characteristics for discrete areas (Elliott et al. 1997; Fralish 1994; McNab et al. 2004; Smalley 1984, 1986; Whittaker 1956; Williard et al. 2005). More recently, advances in digital terrain modeling and mapping have allowed us to combine and analyze the landscape with higher accuracy and precision (Bolstad et al. 1998; Host et al. 1996; Iverson et al. 1997; Kelley et al. 2005; Simon et al. 2005).

By increasing the accuracy of our site quality estimations, we may identify sites with the highest potential productivity, focus our management efforts onto these sites, and reduce the land base used for commercial wood production. As our forests are becoming increasingly important, this work could improve the efficiency with which we utilize our forested resource. In order to manage a forest for any reason, it is imperative to have an accurate inventory.

The objective of this study was to determine if environment-based geospatial estimates of site quality and productivity within a six-county study area in the Blue Ridge of western North Carolina were correlated with estimates from the Forest Inventory Analysis (FIA) data from that area. We hypothesized that site quality predictions generated from three recent indices based on topography and soils would be correlated with estimates taken by the USFS Forest Inventory Analysis plots. A second hypothesis predicted that multiple layers of data (topography and soils) would produce a higher correlation with the validation data. Finally, we felt we would be able to reasonably predict height-driven productivity estimates (site index), but not those derived from diameter (basal area and volume increment).

Methods

Study Area

The six counties chosen for the study included Buncombe, Haywood, Jackson, Madison, Swain, and Yancey, and are located in the mountainous western area of North Carolina known as the Blue Ridge (Figure 1). The terrain is heavily dissected, resulting in maximum elevations around 2000 meters (m). The six counties cover approximately 780,000 hectares, or 34% of the Blue Ridge within North Carolina.

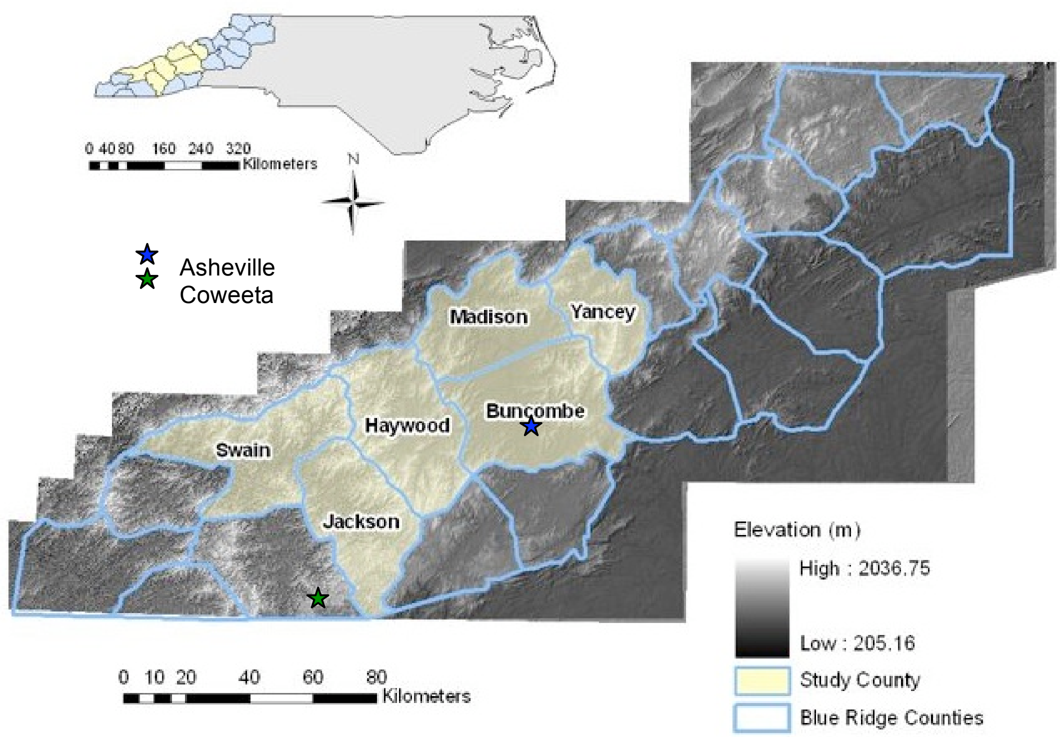

Figure 1: The six counties included in the study area located within the mountains of western North Carolina.

The mean annual temperature is 8 to 16°C and ranges from 3.3°C in January to 24°C in July (USDA NRCS 2006). Precipitation varies widely in the study area and is controlled for plant uptake by the topography. For instance, Asheville, NC, located in the Asheville Basin, receives as little as 900mm of annual rainfall because it is in a rain shadow created by the surrounding mountains (Figure 1). On the other hand, Coweeta Hydrological Laboratory, less than 100 km from Asheville, can receive over 2000mm of annual precipitation, one of the highest rates in the eastern United States. A growing season of 135 to 235 days prevails (USDA NRCS 2006). From the many combinations of topography and landform in the area, aspect significantly affects microclimate, which in turn influences the type and vigor of the vegetation communities. South and west facing slopes are warmer and drier than those found on north and east aspects, as well as those that are shaded by neighboring landforms (USDA NRCS 2006).

General Approach

Several layers of geospatial maps, based on widely available spatial data, were generated. Second, three existing indices were used to predict site quality as a function of the environment for specific locations where there was available FIA data. Finally, the predictions were compared to FIA estimates of productivity.

GIS

An elevation mosaic for the study area was created from 10-meter (m) Digital Elevation Models (DEM's) that were obtained from the USGS National Map Seamless Server. Basic surface analyses, including aspect, slope percent and degree, curvature, and hillshade, were derived from the DEM.

In order to get a measure of slope position (summit, backslope, footslope, etc.) we used the hydrological characteristics of the area. We filled sinks in the DEM and derived flow direction and flow accumulation, in succession. The flow accumulation grid was classified into classes of ½ standard deviation, and a threshold was established to mark the beginning of the streams. The result was then reclassified to create a mask that separated water (NoData) from land (1). The masked flow accumulation was then multiplied by the original flow direction grid, which created a masked flow direction. This was done to allow the water flow to go to the stream edge and stop instead of traveling onto the stream outlet. In essence, we wanted slope position of the land and not the water. Two flow length grids were calculated for downhill and uphill flow length using the masked flow direction. The two length rasters (downhill and uphill) were then used in the formula:

$$\text{Downhill flow length} / (\text{Uphill flow length} + \text{Downhill flow length})$$

This calculation allowed for an estimate of slope position as a percent of the slope, where 0% slope position represented the bottom of the slope at stream edge and 100% was at the ridge top.

Indices Used to Predict Site Quality

Three indices were used to predict the site quality of the study area. They were chosen because they represented site quality and productivity based on water availability, which has been cited as the most limiting factor to tree growth in the southern Appalachians (Smith 1994).

Terrain Shape Index (McNab 1989): The simplest algorithm for determining upland hardwood productivity, the TSI provided a measure of the concavity or convexity of the land that surrounded the plot center. It is defined as the mean slope gradient of the plot boundary as viewed from the plot center (McNab 1989). High values indicated maximum convexity (ridges, spur ridges, nose slopes), and minimum values indicated maximum concavity (creek beds, coves, bottoms). The original development of the model related the TSI to yellow-poplar site index in the Blue Ridge. The formula of the TSI is as follows:

TSI = mean elevation of the plot boundary / plot radius

In ArcGIS, a grid of the TSI function was calculated in raster calculator as:

TSI = [DEM-focalmean (DEM, annulus, 3,4)] / 35

The focalmean is a neighborhood function, which allows a cell-to-cell comparison to determine the answer to the command. The "3,4" portion specified that the plot boundary was to be determined between 30-40m from the plot center and would produce a radius of 35m.

Forest Site Quality Index (FSQI) (Meiners et al. 1984): Meiners and others (1984) examined the effect of topography on available water in the Ridge and Valley of southwestern Virginia and the result was the FSQI. It combined slope position, slope percent, and aspect to determine topographic position as it affected water availability for forest growth. Once the index number was determined it was then correlated to the upland oak site index. This was the only index that categorized all variables and outputs into specific productivity classes.

In ArcGIS, the aspect, slope percent, and slope position grids were reclassified to reflect the assigned FSQI score (Table 1). Adding the three grids together in raster calculator produced the final index grid, which had a potential value range of 3 - 16. A high index value indicated high site quality.

Table 1: Values assigned to the input variables in the FSQI productivity model.

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		

Integrated Moisture Index (IMI) (Iverson et al. 1997): The most complex index of the three, the IMI combined topographic and soils data to get an index of site quality. It was developed in the Alleghany Plateau in Ohio, which should be considered when assigning weights to the input variables. It is the only index that was originally created in a digital environment. From a 10m DEM, we derived hillslope, curvature, and flow accumulation, and from a 1:250,000 STATSGO map, we derived whole-profile available soil water (cm). The four variables were weighted and added in raster calculator to produce a final map of IMI. The authors were able to correlate the index to upland oak site index, and high index numbers indicated high site quality.

FIA Database

Productivity estimates from the North Carolina FIA database were compared to predictions of site quality in the study area (Figure 2). We obtained, for the entire state of North Carolina, the tree, plot, and condition tables for the years of 1982 (Cycle 5), 1990 (Cycle 6), and 2002 (Cycle 7). As part of a Privacy Policy Study Group Memorandum of Understanding, the Southern Research Station FIA unit provided the actual plot locations.

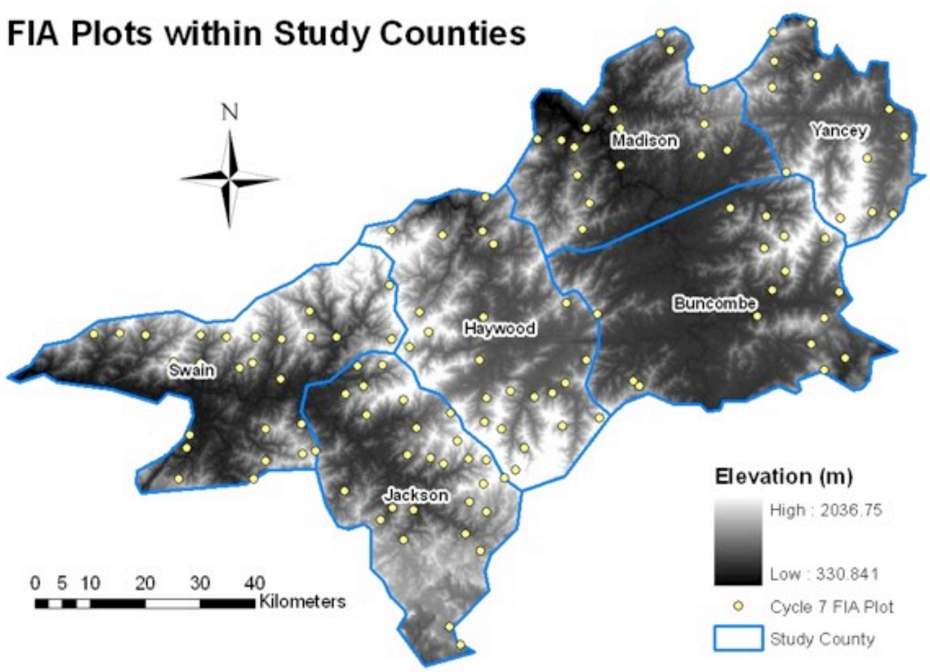

Figure 2: FIA plots used to test the accuracy of the site quality predictions generated by the TSI, FSQI, and the IMI.

FIA productivity estimates used to test the accuracy of the predictions included site index and basal area increment from Cycle 7, and volume increment from a six-year difference between Cycles 5 and 6. A larger increment was preferred but could not be obtained due to a change in survey methodology between Cycles 6 and 7 (from periodic to annual). This resulted in an inability to match trees and plots between the two cycles.

Some stratification of the database was done to ensure that the FIA plots were forested, mostly hardwood, and minimally disturbed (Table 2). Note that Table 2 reflects the number of usable FIA plots within the entire Blue Ridge portion of North Carolina; for the plot sample size that covered the six-county study area, please refer to Table 3. According to the FIA database, stand age is subject to large error because it is difficult to quantify (Forest Inventory and Analysis Program 2008). For this reason, age was not used as a rigid exclusion criterion.

Table 2: FIA database screening criterion and details for forested plots in the Blue Ridge physiographic province for cycles 5, 6, 7, and Merged 5 & 6.

Cycle 5 Criterion	Initial Plot *n*	Plot *n* after screening	Difference (# Plots Deleted)	Percent of initial plot *n* kept
forested land in Bl. Ridge	1025	804	221	
water or balance plot	804	733	71	
>20% conifer BA in plot	733	546	187	
removed tree in plot	546	**495**	51	48.3

Cycle 6 Criterion	Initial Plot *n*	Plot *n* after screening	Difference (# Plots Deleted)	Percent of initial plot *n* kept
forested land in Bl. Ridge	1022	793	229	
water or balance plot	793	735	58	
>20% conifer BA in plot	735	553	182	
removed tree in plot	553	**499**	54	48.9

Cycle 7 Criterion	Initial Plot *n*	Plot *n* after screening	Difference (# Plots Deleted)	Percent of initial plot *n* kept
forested land in Bl. Ridge	930	767	163	
water or balance plot	767	767	0	
one condition only	767	507	260	
no lat/lon recorded	507	482	25	
>20% conifer BA in plot	482	370	112	
removed tree in plot	370	355	15	
stand treatment	355	**347**	8	37.3

Merge 5 & 6 Criterion	Total initial merged plot *n*	Plot *n* after Screening[a]	% of Total initial merged plot *n* kept	No. Counties
Merge Cyc 5 & 6	575	**376**	65.391	23

[a]Screening criteria include unmatching plots and age difference of 6 years, after individual cycle screening criteria were applied

Statistics

Pearson's correlation coefficient *(r)* was calculated to determine the relationship between the FIA productivity estimates (site index, standing basal area, and volume increment) and the predicted site quality estimates which were generated by the TSI, FSQI, and IMI.

Results and Discussion

Digital Imagery of the Productivity Models

The first step of the analysis involved predicting site quality using the TSI, FSQI, and IMI. Maps of predicted site quality were generated in ArcGIS using each of the indices (Figures 3, 4, and 5).

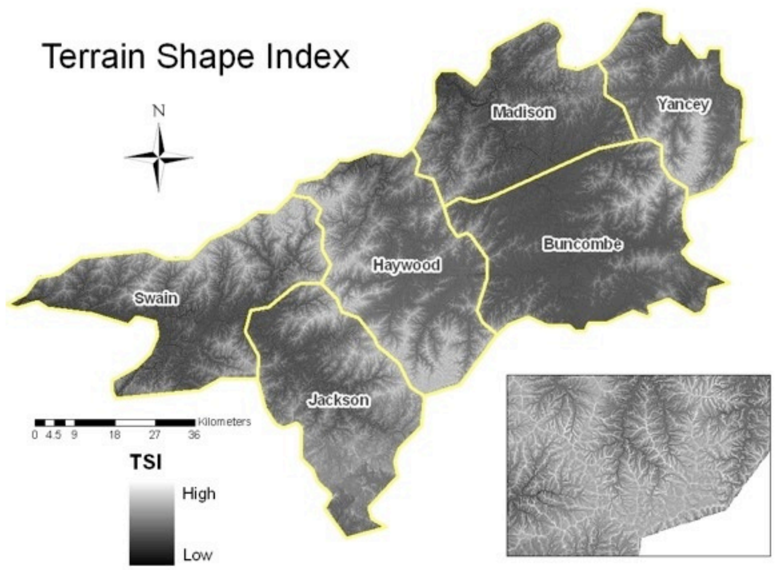

Figure 3: The digital representation of the TSI across the study area.

The TSI model was best represented as a continuous black-to-white grid where high, or light, values indicated maximum convexity, or areas where water would not be stored. Dark, or low values represented maximum concavity, or areas where water would be more accessible for tree uptake and growth. This could translate to a continuous grid of site quality, where high TSI values served as a proxy for low site quality, and low TSI values for high site quality.

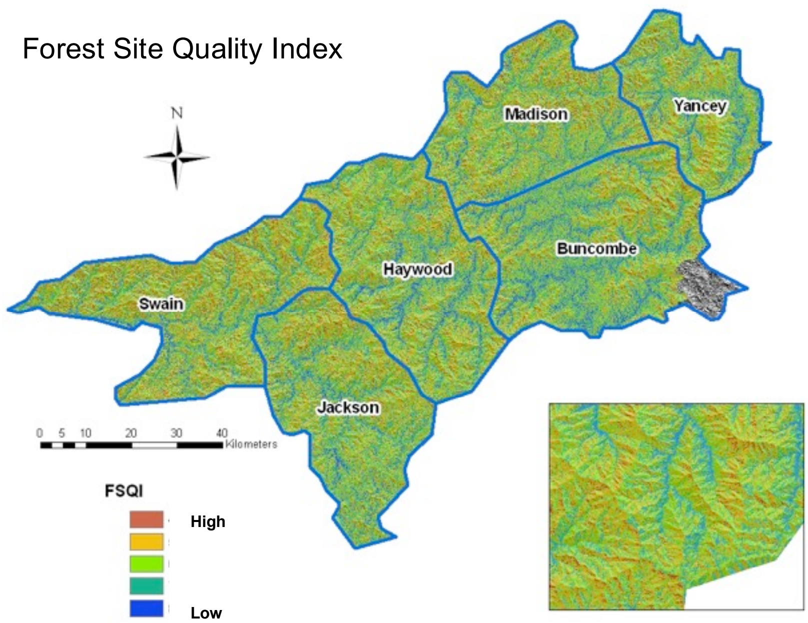

Figure 4: The digital representation of the FSQI across the study area.

The FSQI model was represented as a categorical grid to mirror the final index scores, with cooler colors (blue and green) reflecting higher site quality and warmer colors (red and orange) indicative of lower site quality. This map represents the combination of aspect, slope percent and slope position as they affected water availability, and in turn, site quality.

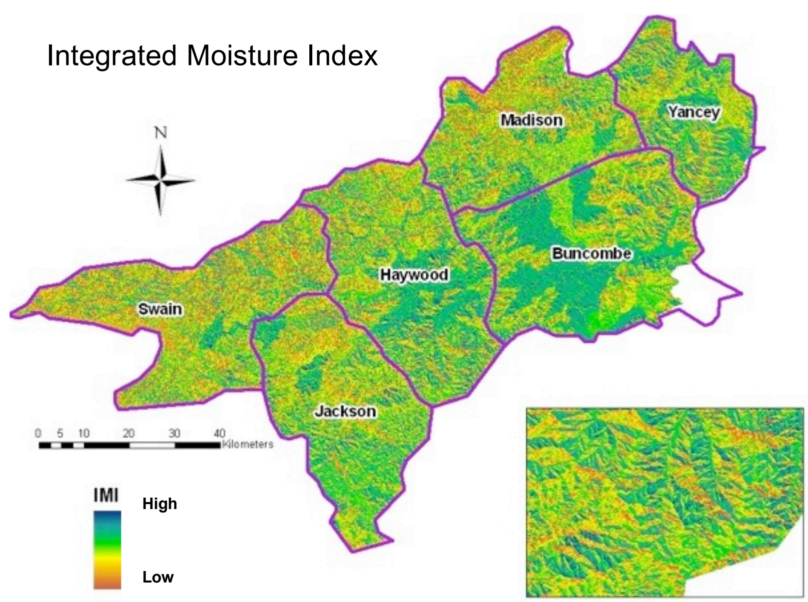

Figure 5: The digital representation of the IMI across the study area.

The IMI model was represented as a continuous color map to show the wide variation of site qualities across the study area. The color scheme mirrored that of the FSQI, where high index scores (demonstrating to high site quality) were depicted in blue and low index scores (low site quality) were in red. The final model grid was a weighted combination of flow accumulation, curvature, whole-profile available water holding capacity, and hillshade. We felt the IMI would have the most power in reflecting the true site quality of the study area; however, it predicted high site quality in the Asheville Basin, which has low site quality due to its landscape position within a rain shadow. Questions emerged at this juncture, in particular, what else was affecting the site quality besides topographic and edaphic conditions?

Correlation Analysis

Of the three FIA estimates of productivity (site index, standing basal area, and volume increment), site index alone was somewhat predictable (Table 3). This was expected since any measure of productivity that is diameter-based will be highly influenced by stand conditions, such as density, stage of succession, management practices, and disturbance history. Comparative analysis through correlation revealed a moderate relationship between the FSQI and FIA site index (Figure 6).

Table 3: Summary of Pearson's correlation coefficients and sample sizes (in parentheses) for predicted versus actual site productivity.

	Predictive Index		
FIA Productivity Estimate	**TSI**	**FSQI**	**IMI**
Site Index	-0.25 (127)	0.38 (143)	0.09 (125)
Standing Basal Area	0.05 (127)	-0.01 (143)	0.18 (125)
Volume Increment	-0.03 (137)	-0.04 (138)	0.05 (148)

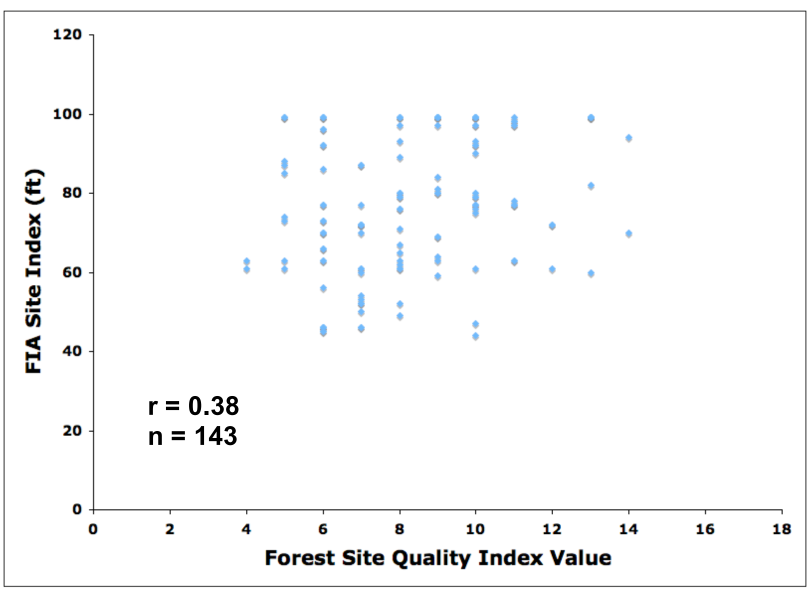

Figure 6: Scatter plot showing the correlation between FIA Site Index and the FSQI.

The correlation between FIA site index and the FSQI could have been higher had the FIA site index not been capped at 99 feet (Figure 6). Discussions with FIA personnel indicated that at some point site index values had been allocated only two numeric digits, limiting site index to a maximum of 99 (pers. comm., Ray Sheffield, USFS SRS FIA). Further, considering that we were working with a wide range of hardwood species as well as age classes, we felt that 0.38 was a reasonable correlation.

The TSI did not correlate with any of the FIA estimates of productivity (Table 3). We could not use this model to predict the actual site index for the study area because of the larger area, more extreme terrain values, and issues with replicating the index digitally, which produced more extreme values than what McNab originally derived in his model development. Because of this, a decision was made to use the calculated index values versus the model calculated site index for all of the correlations to maintain consistency.

Unexpectedly, the addition of soils information did not improve the predictive ability of the IMI (Table 3). This was likely a result of the scale of the STATSGO data layer (1:250:000). This particular index may have had more power if finer-scale data, such as SSURGO, (scale of 1:25,000) could better reveal differences that may exist among the mapping units. Additionally, it is necessary to account not only for the capacity of a soil for water storage, but for usage and inputs to that system as well, as was exemplified with high IMI value for the rain-shadowed Asheville Basin. We feel by incorporating all aspects of the water cycle (inputs of climate, usage in the form of evapotranspiration, and storage as defined by the environment and soils), we will come closer to predicting the true site quality of these forested ecosystems.

Overcoming Issues to Progress Forward

Productivity and site quality research shows promise using FIA data but there are some issues that need to be resolved in order for this database to be truly workable in such an environment. Specifically, the inability to match trees between the periodic and annual surveys restricts the calculation of any reasonable growth increment to capture productivity. The site index estimates as taken in the field are subject to considerable error, but they are the best we have for this study. Changed plot numbers between the two survey methods also hinders analyses between cycles. Finally, a consistent way to capture plot age would be helpful when dealing with stands of mixed-species and mixed-aged hardwoods. This is a subjective task at best, but perhaps if a protocol were established by the FIA, our site quality predictions for upland hardwoods would be more robust.

Conclusions

As hypothesized, site quality predictions generated by the FSQI were reasonably correlated with the FIA data. Second, we were able to predict site index but not basal area or volume increment. Finally, additional information about soils did not improve the predictive ability of the Integrated Moisture Index, mainly due to the coarse scale of the data.

These findings indicate that more work is needed to predict site quality as a function of environment in the upland hardwood forests of the southern Appalachians. Future efforts to capture this model include the incorporation of water usage and inputs in the form of evapotranspiration and climate, respectively. Further, the use of more detailed and different types of soils information, such as SSURGO, may allow for better explanation of how water is stored in the forest, and how it affects site quality. This data may also refine the predictions by providing a measure of nutrient availability through the characteristics of soil organic matter content, texture, and depth. Along these lines, geofertility classes based on parent material are being considered as well.

Site quality and productivity work in the southern Appalachians has been continuous for at least the past one hundred years. The significance of this work is even more important now as our forests are valued for multiple products, such as a timber, clean water, wildlife habitat, carbon stores, and recreation. As our estimates of site quality increase, we will be able to more effectively partition the forest into efficient management units so all usage objectives may be met for the long term. It is imperative we sustain our forests for future generations, and this work will directly affect that goal.

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