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Modeling forest site productivity using mapped geospatial attributes within a South Carolina Landscape, USA

B.R. Parresol[a,1], D.A. Scott[b,*], S.J. Zarnoch[c], L.A. Edwards[d], J.I. Blake[e]

[a] USDA Forest Service, Pacific Northwest Research Station, Portland, OR, USA
[b] USDA Forest Service, Southern Research Station, Normal, AL 35762, USA
[c] USDA Forest Service, Southern Research Station, Clemson, SC 29634, USA
[d] USDA Forest Service, Southern Research Station, Asheville, NC 28804, USA
[e] USDA Forest Service, Savannah River Site, New Ellenton, SC 29809, USA

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ABSTRACT

Spatially explicit mapping of forest productivity is important to assess many forest management alternatives. We assessed the relationship between mapped variables and site index of forests ranging from southern pine plantations to natural hardwoods on a 74,000-ha landscape in South Carolina, USA. Mapped features used in the analysis were soil association, land use condition in 1951, depth to groundwater, slope and aspect. Basal area, species composition, age and height were the tree variables measured. Linear modelling identified that plot basal area, depth to groundwater, soils association and the interactions between depth to groundwater and forest group, and between land use in 1951 and forest group were related to site index (SI) ($R^2 = 0.37$), but this model had regression attenuation. We then used structural equation modeling to incorporate error-in-measurement corrections for basal area and groundwater to remove bias in the model. We validated this model using 89 independent observations and found the 95% confidence intervals for the slope and intercept of an observed vs. predicted site index error-corrected regression included zero and one, respectively, indicating a good fit. With error in measurement incorporated, only basal area, soil association, and the interaction between forest groups and land use were important predictors ($R^2 = 0.57$). Thus, we were able to develop an unbiased model of SI that could be applied to create a spatially explicit map based primarily on soils as modified by past (land use and forest type) and recent forest management (basal area).

1. Introduction

Many forest management decisions require a spatially explicit estimate of forest site productivity, or mean annual increment of growth over a defined interval, to assess species-site suitability, silvicultural alternatives, carbon sequestration capacity, wildlife habitat suitability and climate impacts. Spatially explicit estimates of forest productivity across entire landscapes are a challenge as direct measurement of growth potential and associated soil chemical or physical properties are traditionally expensive and, therefore, limited to smaller inventory samples (Swenson et al., 2005). Although remote sensing technology like LiDAR (Light Detection and Ranging) can measure tree heights with great precision and resolution over large landscapes, it is not widely adopted for estimating potential productivity at this time due to the need to extensive field plot calibration (Gatziolis, 2007). Geospatially-mapped attributes of climate, soil, topography, prior land use and silviculture treatment offer an opportunity to cost-effectively create spatially explicit landscape estimates of productive potential for management. However, they may not reliably represent causal variables, as their accuracy and precision is often unknown and they scale differently in relation to their effects on productivity (Aertsen et al., 2012).

Several studies have estimated productivity over very large climate gradients. Site index (SI) is the most commonly used, relatively density-independent quantitative indicator of site productivity (Avery and Burkhart, 2002). Site index for Norway spruce (*Picea abies* (L.) Karst) was modelled successfully over Bavaria, Germany using a combination of temperature, water supply and soil base saturation parameters derived from mapped features (Brandl et al., 2014). Site index for cork oak (*Quercus suber* L.) was predicted across Portugal using a combination of derived water availability and soil properties obtained from large thematic maps of climate and geology (Paulo et al., 2015). Soil water availability was derived from mapped climate conditions and soil

* Corresponding author.
E-mail address: andyscott@fs.fed.us (D.A. Scott).
[1] Deceased.

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units to estimate SI across the southern USA for managed and unmanaged loblolly pine (*Pinus taeda* L.) (Sabatia and Burkhart, 2014). A regional model of SI for conifers and hardwoods across the eastern USA was created by modeling SI values obtained from U.S. Forest Service, Forest Inventory and Analysis data with climate and soil variables (Jiang et al., 2015).

In contrast, successful attempts to use mapped geospatial attributes under identical climate conditions to predict productivity are limited (Payn et al., 1999). In the southeastern USA, mapped taxonomic soil series are weakly related to species productivity (Van Lear and Hosner, 1967). However, predictive relationships can be found if specific soil conditions are measured. In the coastal plain, depth of organic layers or depth of the argillic horizon are related to productivity (Coile and Schumacher, 1953; Shoulders and Tiarks, 1980). In high water table regions, drainage conditions and phosphorus availability are important predictors (Comerford and Pritchett, 1982; Morris and Campbell, 1991). A combination of chemical and physical soil properties within the upper 15 cm of the mineral soil was strongly correlated to site index across 15 loblolly pine plantations in the southern USA (Subedi and Fox, 2016). Unfortunately, these chemical or physical soil attributes are rarely mapped over the landscape or sampled sufficiently to represent the variability in these attributes. Landscape attributes that control productivity are also confounded by prior agricultural land use and forest management treatments (Clutter and Dell, 1978; Martin and Jokela, 2004).

The goal of this research was to create a reliable model that enabled the construction of a spatially-explicit map of SI. A spatially continuous Modeling process, such as continuous cartographic Modeling or generalized kriging, requires representative observations for the entire landscape (Kemp, 2008). Therefore, our objective was to determine if SI measurements from inventory plots were related to mapped soil, groundwater, stocking, prior land use and forest group attributes across a continuous landscape in South Carolina, USA within identical climate conditions.

2. Methods

2.1. Site description

The study location was the U. S. Department of Energy, Savannah River Site (SRS), an 80,000-ha National Environmental Research Park in South Carolina (Kilgo and Blake, 2005). It is located on the Upper Coastal Plain and Sandhills physiographic provinces in South Carolina, USA (Fig. 1). The site was established in 1950 and managed for various natural resources compatible with the Department of Energy defense missions associated with the processing, storage and disposition of nuclear materials (USDA Forest Service - Savannah River, 2005). Agrarian practices have impacted more than 70% of the landscape since European settlement in the late eighteenth century (White and Gaines, 2000). When the SRS was established, approximately 33,000 ha were in farm fields with the balance in cutover forest with low stocking and some intact forests (Kilgo and Blake, 2005). Only about 2000 ha were in pine plantations in 1950; these plantations were established on farm fields between 1938 and 1948.

Currently, three major forest types are present: pine plantation, mixed pine-hardwood forest, and hardwood forest. Of the 80,000 ha at SRS, about 74,000 ha are classified into one of these three categories and are mapped as about 6000 discrete stands. Between 1951 and 1970 the agricultural fields and cutover forests were converted to plantations of loblolly pine, longleaf pine (*P. palus*tris Mill.) and slash pine (*P. elliottii* Engelm. var. *elliottii*) with limited or no attention to soil conditions. This practice resulted in plantations of the three pine species (> 80% pine) in adjacent stands throughout the landscape. Site preparation on these areas consisted of mechanical furrows or disking to provide weed control and bare soil for planting. Treatment of hardwood tree competitors with herbicides occurred on cutover forest sites, but these treatments did not impact shrub or grass competition with planted trees. Disking and raking of residual debris occurred in the 1980's and early 1990's followed by an application of herbicide and then prescribed fire prior to machine planting. There was no operational planting of genetically improved high yield pines or routine fertilization. Mixed pine-hardwood forest exist predominately in upland woodlots adjacent to old farm fields in a continuous gradient down through riparian zones, but are present in on old farm field due to natural regeneration. These stands are distinct from the plantations because they represent natural regeneration of loblolly pine intermixed with various hardwood species such as oaks (*Quercus* spp.), hickories (*Carya* spp.), sweetgum (*Liquidambar styraciflua* L.) and occasional longleaf pines. Finally, hardwood-dominated forests have fewer pines (< 20% pine by stocking). They are similar to mixed pine-hardwood forests in composition and are harvested periodically and regenerated naturally.

The current land management objectives include support for the Department of Energy defense and research missions, a continuous stream of revenue, recovery of endangered and threatened species and restoration of important habitat conditions for plants and animals (USDA Forest Service - Savannah River, 2005). Today, rotation ages range from 50 to 120 years depending upon management area and species. Intermediate thinning and clear felling occurs on about 2000 ha and 300 ha, respectively, each year (Kilgo and Blake, 2005). Where clear felling is conducted, site preparation currently consists of a single application of herbicide followed by burning. Longleaf pine, loblolly pine or various hardwood species are then planted. When intermediate thinning is performed, smaller diameter and poorer quality trees are preferentially removed, subject to maintaining spacing between trees. First thinning begins between ages 15 and 30 years with subsequent thinning done periodically at 10- and 20-year intervals, depending upon stocking levels.

2.2. Site productivity

Site index, the mean height of dominant and co-dominant trees at a standard age of 50 years, was used as an indicator of site productivity. In 2000, we conducted a forest inventory of the entire SRS from which we obtained SI data (Parresol et al., 2012). Plots were established on a 1000-m × 1000-m grid across the entire SRS, resulting in more than 600 geo-referenced plots across the landscape (Fig. 1). A plot consisted of a cluster of five subplots spaced 21.3 m apart along a line within a stand of the same forest type and age. A variable-radius prism measurement with an 8.61 basal area (BA) factor ($m^2\ ha^{-1}$) was used for sampling overstory trees. All prism samples from the five subplots were combined. Subplot measurements included BA, total tree height, diameter at breast height (DBH), and species for all prism trees. Tree age at DBH (1.3 m above ground) was determined from tree cores for two to eight selected, apparently undamaged, dominant or codominant trees within the five subplots.

Pine trees, when available as dominants or co-dominants, were selected for determining SI. This led to 2361 SI trees representing 53% loblolly, 25% longleaf, 15% slash pine and 7% various hardwood species. We excluded SI sample trees under 18 and over 95 years old due to unreliable SI estimates at these ages. This restricted the population to plantations and naturally regenerated stands established prior to 1980. For the mixed pine-hardwood forest group (50 plots) we excluded hardwood trees and retained only pine SI values which led to a distribution of pine SI trees that were approximately 80% loblolly pine, 15% longleaf pine and 5% slash pine trees. We calculated SI from core age and total height using Carmean's SI prediction equations at base age 50 for the individual tree species (Carmean et al., 1989). The equations used within his publication are: loblolly pine, Fig. 111; longleaf pine, Fig. 93; slash pine, Fig. 85; white oak (Q. alba) Fig. 37; southern red oak (*Q. falcata* Michx.), Fig. 37; laurel oak (*Q. laurifolia* Michx.), Fig. 44; black oak (*Q. velutina* Lam.), Fig. 49; post oak (*Q. stellata* Wangenh.),

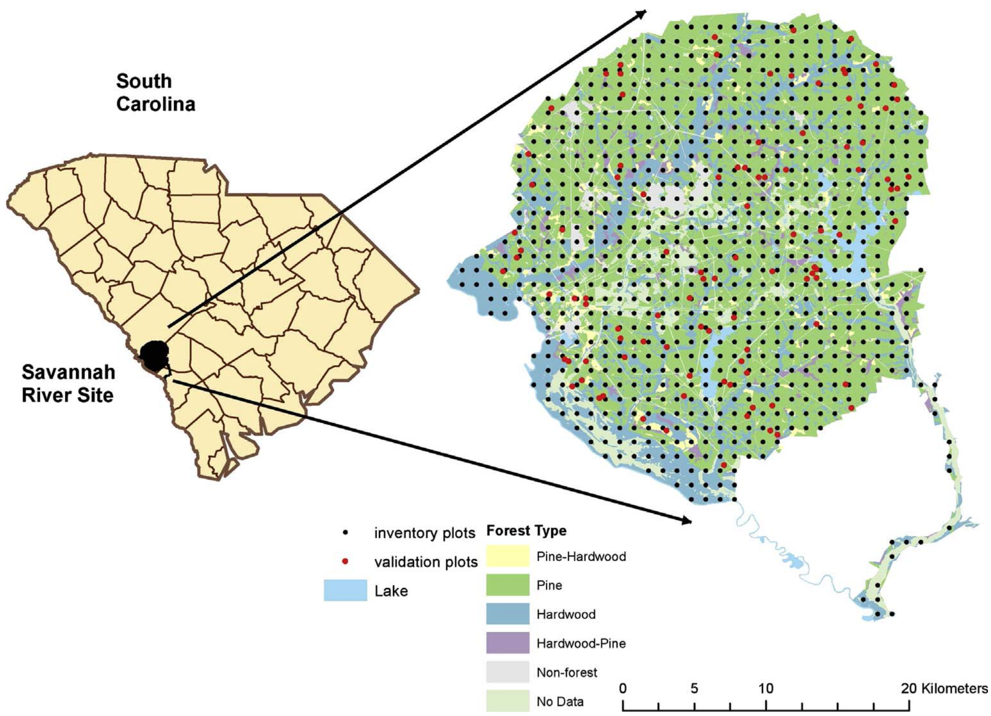

Fig. 1. Location map showing the Savannah River Site and distribution of major forest types. Inventory plot locations in 2000 are indicated by black dots, which are established on a 1 × 1 km grid. The 2010 inventory validation plots are in red. Pine-hardwood and hardwood-pine types were combined in the analysis to form a single forest group due to the limited number of plots.

Fig. 46; hickory spp., Fig. 10; sweetgum, Fig. 21; and black gum (*Nyssa sylvatica* Marshall), Fig. 26. The SI for each plot was calculated as the average SI of all trees. The final dataset for modeling consisted of 587 plots.

A validation dataset was obtained from a new inventory conducted in 2010 consisting of 1679 geo-referenced inventory plots established on a systematic grid across the entire landscape (Fig. 1). These plot locations were not coincident with the previous inventory plots and were designed primarily to obtain sub-canopy information and construct models of overstory-understory relationships. Each plot included a single prism point estimate ($2.3\ m^{-2}\ ha^{-1}$ factor) of overstory BA, tree DBH, and species. We selected 100 of these new plots at random to measure SI to create an independent validation data set. Within these plots, cored age and total height were obtained for three to four dominant and co-dominant trees per plot. For purposes of the validation objective, we deleted hardwood plots and hardwood trees since our primary interest was the pine forest groups. This procedure resulted in retention of 89 plots with 270 SI trees that consisted of 59% loblolly, 32% longleaf, and 9% slash pine. We calculated SI in the previous manner.

2.3. Geospatial data

The geospatial layers that provided independent variables for Modeling SI were created as raster layers or converted from vector to 20-m raster layers. The SRS historical land use-land cover (LULC) dataset was derived from a mosaic of 13 scanned, rectified, and georeferenced black and white aerial photos taken in May 1951 at a scale of 1:20,000. Eight LULC types were classified (i.e. closed canopy, cutover forest, open agriculture, orchards, industrial, farm, Carolina bays, and water) with objective oriented feature extraction Modeling procedures (Intergraph, 2013). Of the eight LULC types, only three were relevant to the managed forest: closed canopy forest, open agriculture, and cutover forest. The other LULC types were orchards, Carolina bays, developed-industrial, developed-farm and water. To create a continuous raster layer of forest species types we assigned every stand into one of five forest groups (FTGRP) based on historical stand exams of species and relative basal area: 80% or more loblolly pine, 80% or more longleaf pine, 80% or more slash pine, mixed pine-hardwood with 20–79% pine and hardwood < 20% of the basal area. The assignment of a stand to an FTGRP was done without reference to LULC or any other independently mapped variables used in the modeling.

Soil association (SA) data were obtained from the U. S. Department of Agriculture, Natural Resource Conservation Service (NRCS) 1:190,080 general soil map of SRS, which was a digitized vector layer converted to a 20-m raster grid (Rogers, 1990). Approximately 50 taxonomic soil series are found on the SRS, and are classified into one of seven SAs by the NRCS according to their criteria for texture, drainage, landscape position and other features of soil pedogenic development. These SAs are Chastain-Tawcaw-Shellbluff representing poorly drained and somewhat poorly drained soils that are subject to flooding; Rembert-Hornsville representing poorly drained and moderately well drained soils that have clayey subsoil; Blanton-Lakeland representing excessively drained soils; Fuquay-Blanton-Dothan representing well drained and somewhat excessively drained soils that have loamy subsoil; Orangeburg representing well drained soils that have loamy subsoil; Vaucluse-Ailey representing well drained soils that have a loamy subsoil with dense, brittle layers; and finally, the Troup-Pickney-Lucy that represents a mixture of both well drained soils on slopes and very poorly drained soils in adjacent floodplains.

Depth to the groundwater (DGW) was collected from more than 1300 wells distributed over the SRS. The elevation and location for each well was surveyed and a continuous groundwater elevation layer relative to the surface elevation was mapped through interpolation over the landscape (Hiergesell and Jones, 2003). Adjacent to streams, riparian zones and the Savannah River, DGW could appear negative since the inventory plot elevations were derived from a more precise digital elevation model (DEM) generated from a 2009 LiDAR overflight (Reutebuch and McGaughey, 2012). The LiDAR data was collected at 6 pulses m^2 and could resolve difference in elevation of < 15 cm. To avoid negative values, 0.5 m was added to the mapped DGW values. The DGW varied from 0 to 48 m below the surface with the greatest range in upland areas between perennial streams and the smallest range adjacent to perennial streams.

Other variables included plot slope, aspect, and BA. Plot slope (%) and aspect (eight 45° categories, e.g. N 337.5°–22.5°, NE 22.5°–67.5°, etc.) were determined at each main plot from a DEM generated from the 2009 LiDAR overflight at the scale of 5-m and aggregated to 20-m. Topographic data was managed with ArcGIS ERSI version 10.3.1 (http://desktop.arcgis.com/en/arcmap/10.3/). We used BA to account for potential stocking effects on SI because of the known impact of high stocking levels on depressing height growth in southern species (Brooks and Bailey, 1992).

2.4. Statistical analysis and cartographic mapping

We performed an iterative statistical analysis on the full data set of 587 plots and separately on the subset of 255 loblolly pine plots. SI modeling started with a suite of plot attributes that were mapped at the landscape level: LULC, SA, FTGRP (categorical variables) and plot slope, aspect, BA and DGW (continuous variables). Various transformations (square root, inverse, natural logarithm) were applied to BA as its biological effects on height development were not anticipated to be simple linear functions over the range of data. The linear model selection process was performed using PROC GLMSELECT in SAS via backward elimination (SAS Institute Inc., 2009). The Akaike's information criteria (AIC_C) which has a correction for sample size was used to guide selection of the variables to retain. All two-way interaction terms were included in the model evaluation. We kept the variables in the model if the significance was less than 0.1. Fit diagnostics for the final model were investigated by examining residuals, including the correlation of the residuals with the predicted SI. Slope and aspect were dropped from the initial runs as these variables were strongly collinear with DGW.

Comparison of observed vs. predicted SI and the residuals indicated that there was a bias in the regression model. This is often due to regression attenuation which is a biasing of the regression slope parameter of a variable towards zero due to measurement error in the independent variables (Buonaccorsi, 2010). The two continuous variables, BA and DGW, have known sources of measurement error. The BA error results from sampling variability within stands. The DGW error results from geospatial projection of the DGW coupled with the seasonal-annual variability in DGW. Methods commonly used for correction of regression attenuation require an estimate of the measurement error variance of the independent variable from either a separate validation data set, repeated measurements or an instrument variable (Buonaccorsi, 2010). We estimated the BA measurement error variance (60.13) from the five subplot measurements within each plot by using a two-stage nested model which yielded the between-plot and within-plot variance components using PROC MIXED (SAS Institute Inc., 2009). Since the BA variable is the mean of the five subplot BA observations, its measurement error variance is defined as the within plot variance divided by five. The DGW measurement error variance term (14.09) was estimated as the mean square error of the regression of 27 independently installed wells (validation data set) against the predicted DGW at each geospatial point from the SRS map (Hiergesell and Jones, 2003).

Regression attenuation bias in multivariate models can be corrected within a structural equation modeling (SEM) framework by constructing a latent variable involving the measurement error variance term (McDonald et al., 2005). Structural equation modeling is an extension to multivariate regression that evaluates/estimates complex relationships with direct and indirect pathways between the observed variables as well as unobserved latent constructs. We incorporated the error terms into an SEM modeling framework via PROC CALIS to predict SI and create new parameters (SAS Institute Inc., 2009) (Fig. 2). SEM cannot use multi-class categorical variables per se so we created a set of comparable model dummy variables for each of the variables FTGRP, SA and LULC in PROC GLM and PROC CALIS. Each set was developed by assigning a base to one of the classes in the variable and then developing binary dummy variables (0, 1) for each of the other classes in that variable. The set of four dummy variables for FTGRP used mixed pine-hardwoods as the base, the set of two dummy variables for LULC used closed canopy forest as the base and the set of six dummy variables for SA used Blanton-Lakeland soils as the base. We used the variables and interactions obtained from the linear model to represent the SEM model.

The SEM corrected models (full data set of 587 plots and the restricted subset of 255 loblolly plots) were then used to predict SI values, respectively, for the original 587 plots and for the 255 loblolly pine plots. We subsequently examined the residuals to confirm if the bias adjustment was successful. The dummy variable parameter estimates (path coefficients) were tested to determine if they were different from zero for both uncorrected and corrected models. We computed main effect tests of the categorical variables (FTGRP, SA, LULC and their interactions) by simultaneously testing the individual dummy variables using the SIMTEST statement in PROC CALIS, which provides a chi-square test and p-value instead of the typical F-test (SAS Institute Inc., 2009). If the effects were not significant (alpha = 0.1) we eliminated the variable. We then confirmed that the restricted model was more parsimonious by comparing AIC_C values to the full model values. The final uncorrected and corrected model parameters for the full model with 587 plots were used to predict SI for the 89 validation plots. We compared several fit statistics for the two models and the confidence interval for the slope relative to 1.0 and intercept relative to 0.0. Finally we used simple cartographic modeling procedures to map the predicted

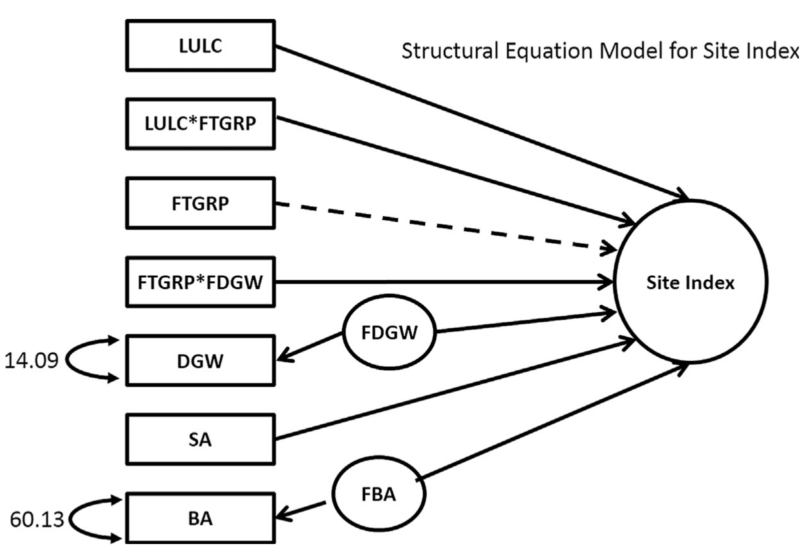

Fig. 2. Structural equation model for site index to adjust regression parameters for measurement error of 60.13 for basal area (BA) and 14.09 for depth to groundwater (DGW). Latent variables are FBA and FDGW. Categorical variables are land use-land cover (LULC) in 1951, soil association (SA) and forest species group (FTGRP). Dashed line designates that FTGRP was a non-significant main effect ($p > 0.10$) in the original linear model. Categorical variables were represented as individual dummy variables in the actual model.

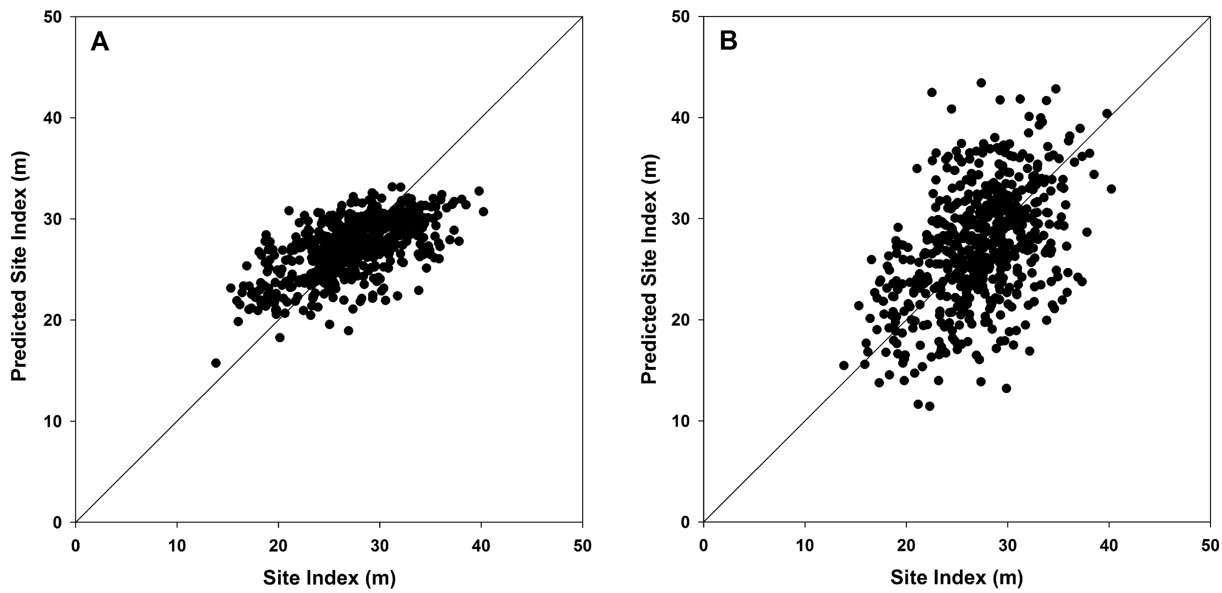

Fig. 3. Predicted site index vs. observed site index values derived from an uncorrected structural equation model that shows regression attenuation bias (A) and when measurement errors for basal area and depth to groundwater were incorporated to reduce attenuation bias (B).

SI using the final corrected model (Kemp, 2008). In this procedure the SI values are calculated for each spatial cell using the model variables at the corresponding 40-m rasterized grid scale.

3. Results

Based on the linear model, the BA ($p < 0.0001$), DGW ($p < 0.0001$), SA ($p = 0.0405$) and LULC ($p < 0.0001$) main effects as well as the interactions FTGRP∗DGW ($p = 0.0084$), and FTGRP∗LULC ($p < 0.0001$) were all related to SI. The overall model provided an R^2 of 0.37, explaining about one-third of the variation in SI point estimates across the 74,000-ha landscape with the five mapped variables. The residuals were strongly correlated to the observed SI values demonstrating regression attenuation bias (Fig. 3a). Predicted SI was over-predicted at low observed SI values and under-predicted at high observed SI values. We did not find any transformation of BA that improved the model.

The SEM uncorrected model also had an R^2 of 0.37 and the same parameter estimates, although p-values changed slightly (Table 2). The continuous variable parameter estimates were tested for differences from zero while the categorical parameter estimates for FTGRP, SA, and LULC were compared against their bases (mixed pine-hardwoods, Blanton-Lakeland soil, and closed canopy forest, respectively) (Table 2). The SI increased with BA and decreased with DGW. The FTGRP∗DGW interaction was strongly related to SI, except for the hardwood∗DGW (Table 2). Predicted SI for the Rembert-Hornesville and Fuquay-Blanton-Dothan SAs were 1.9 and 1.2 m greater, respectively, than SI for the base condition, the Blanton-Lakeland SA (Table 2). The relative rank for SAs main effects was Rembert-Hornesville > Chastin-Tawcaw-Shellbluff > Fuquay-Blanton-Dothan > Orangeburg > Vaucluse-Aikey > Troup-Pickney Lucy > Blanton-Lakeland (Fig. 4). LULC had no strong influence on SI across all conditions (Table 2). However, the interaction between FTGRP∗LULC was evident. In loblolly pine, longleaf pine and hardwoods on open agricultural lands the interaction parameters were greater than on cutover forests relative to the base condition, but the magnitude of the effect varied by species (Fig. 5). On open agricultural sites, loblolly pine SI was greater than loblolly pine SI on cutover forests for both the uncorrected (2.1 m) and error-corrected (2.8 m) analyses. The equivalent SI differences between open agriculture and cutover forest for longleaf pine were 5.9 m and 6.3 m for the uncorrected and corrected models, respectively. In contrast, there appeared to be a much smaller interaction for slash pine. Within closed canopy forest, only the longleaf pine and hardwoods were different than the base condition using the uncorrected model parameters.

For the model with all FTGRPs, formulation of the SEM with measurement errors correction for BA and DGW resulted in a higher R^2 (0.57) as a consequence of the reduction in the error variance assigned to SI and an apparent better fit to the data with respect to predicted versus observed values at high and low SIs (Fig. 3b). The model also had a lower AIC_C. The intercept changed from 23.97 m to 10.83 m (Table 2). The slope parameter for BA increased from 0.1248 to 0.5947. In contrast, the slope parameter for DGW changed from −0.9067 to 0.0162 and was no longer different from 1. The regression attenuation

Table 1
Mean (standard deviation) of continuous variables and distribution of site index plots among class variables obtained from the 2000 (587 plots) and 2010 (89 plots) inventories at the Savannah River Site.

Variable	2000 Inventory	2010 Inventory
Continuous variables	Mean	Mean
Site index (m) 50 years base age	27.2 (4.6)	25.7 (3.3)
Mean basal area ($m^2\ ha^{-1}$)	23.0 (9.7)	23.6 (9.6)
Depth to groundwater (m)	3.6 (2.7)	3.7 (2.4)
Age at breast height	41.3 (18.8)	48.3 (16.9)
Class variables	# plots	# plots
Forest group		
Loblolly Pine	255	47
Longleaf Pine	126	25
Slash Pine	58	8
Mixed Pine-Hardwood	50	8
Hardwood	98	1
Land Use-Land Cover 1951		
Open Agriculture	235	43
Closed Canopy Forest	75	3
Cutover Forest	277	43
Soil Association		
Chastain-Tawcaw-Shellbluff	7	0
Rembert-Hornsville	37	12
Blanton-Lakeland	134	13
Fuquay-Blanton-Dothan	287	48
Orangeburg	11	2
Vaucluse-Ailey	58	9
Troup-Pickney-Lucy	53	5

Table 2
Site index model parameters, standard errors, p-values and model fit statistics for all forest groups using structural equation modeling (SEM) with and without basal area and depth to groundwater measurement error correction. Parameter values p-values represent the probability that the parameter estimate is significantly different than zero. Main effect p-values are for the chi-square test of the combined class or dummy variables.

N = 587 Plots	Without error correction			With error correction		
Variable	SEM parameter	Std. error	P value	SEM parameter	Std. error	P value
Intercept	23.9700	1.1972	< 0.0001	10.8310	4.1778	0.0095
Basal area ($m^2\ ha^{-1}$) (BA)	0.1248	0.0172	< 0.0001	0.5947	0.1475	< 0.0001
Depth to groundwater (m) (DGW)	−0.9067	0.2221	< 0.0001	0.0162	0.0121	0.1809
Soil association (SA)	Main effect p-value = 0.0309			Main effect p-value = 0.0949		
Chastain-Tawcaw-Shellbluff	1.8123	1.5258	0.2349	2.2438	2.2998	0.3292
Rembert-Hornsville	1.8776	0.7289	0.0100	1.4942	1.1134	0.1796
Blanton-Lakeland	0.0000	–	–	0.0000	–	–
Fuquay-Blanton-Dothan	1.2347	0.4034	0.0022	1.5937	0.6185	0.0100
Orangeburg	1.0578	1.1680	0.3652	0.4201	1.7724	0.8126
Vaucluse-Ailey	0.6053	0.5949	0.3089	0.1641	0.9066	0.8574
Troup-Pickney-Lucy	0.2324	0.6266	0.7107	−0.5711	0.9891	0.5644
Land Use-Land Cover (LULC)	Main effect p-value = 0.5770			Main effect p-value = 0.8289		
Open Agriculture (OA)	1.7993	1.9253	0.3500	1.5806	2.8419	0.5781
Closed Canopy Forest (CCF)	0.0000	–	–	0.0000	–	–
Cut-Over Forest (COF)	1.2035	1.3330	0.3666	1.0377	1.9436	0.5934
Forest Group	Main effect p-value = 0.8938			Main effect p-value = 0.3768		
Loblolly Pine	−0.2792	1.4006	0.8420	−0.9200	2.1379	0.6670
Longleaf Pine	0.9273	2.8450	0.7445	7.1396	4.5853	0.1195
Slash Pine	2.2074	2.8997	0.4465	3.0260	4.3601	0.4877
Mixed Pine-Hardwood	0.0000	–	–	0.0000	–	–
Hardwood	−0.3999	1.1562	0.7294	−1.5081	1.8140	0.4058
Forest Group × DGW Interaction	Interaction effect p-value = 0.0060			Interaction effect p-value = 0.7996		
Loblolly Pine*DGW	0.7592	0.2391	0.0015	−0.0626	0.1467	0.6694
Longleaf Pine*DGW	0.8325	0.2538	0.0010	−0.0851	0.1843	0.6442
Slash Pine*DGW	0.6376	0.2944	0.0281	−0.3108	0.2842	0.2741
Mixed Pine-Hardwood*DGW	0.0000	–	–	0.0000	–	–
Hardwood*DGW	0.3880	0.2793	0.1647	0.0718	0.3232	0.8260
Forest Group × LULC Interaction	Interaction effect p-value = < 0.0001			Main effect p-value = 0.0038		
Loblolly Pine*OA	1.2208	2.1803	0.5755	3.6834	3.1306	0.2384
Longleaf Pine*OA	0.3306	3.2681	0.9194	−0.3029	4.9404	0.9511
Slash Pine*OA	−4.3355	3.2753	0.1856	−3.6159	4.8788	0.4586
Mixed Pine-Hardwood*OA	0.0000	–	–	0.0000	–	–
Hardwood*OA	0.2893	2.3540	0.9022	3.8929	3.4037	0.2527
Loblolly Pine*COF	−0.9261	1.6770	0.5808	0.8848	2.3744	0.7494
Longleaf Pine*COF	−5.5915	2.9513	0.0581	−6.6062	4.5003	0.1362
Slash Pine*COF	−4.4706	3.0996	0.1492	−1.6934	4.5868	0.7120
Mixed Pine-Hardwood*COF	0.0000	–	–	0.0000	–	–
Hardwood*COF	−2.8217	1.6039	0.0785	−1.6615	2.2842	0.4670
Fit Statistics						
Akaike's Information Criteria	810			810		
[a]R^2	0.3718			0.5713		
P-Value	< 0.0001			< 0.0001		

[a] R^2 = (1 − (Error Variance SI/Total Variance)).

correction inflated the standard error for the categorical variables leading to an increase in the p-values for most of those variables. We deleted the DGW variable and its' interactions and the FTGRP from the full corrected model with 587 observations to create a more parsimonious model and this step improved the AIC_C (304 vs. 810), but not the R^2 or p-value.

We removed the non-significant main effect variables and interaction from the model based on a p-value of 0.1, which lead to the deletion of FTGRP and LULC in the uncorrected model and DGW, FTGRP, LULC and the interaction of DGW∗FTGRP in the corrected model (Table 2). We recomputed the model parameters to create a more parsimonious model to estimate the effect of BA or stocking level on SI. The overall effect of stocking level or BA for loblolly pine in closed canopy LULC conditions on the most common SA (Fuquay-Blanton-Dothan) were computed. For this species, SI values changed by 10 m or more over the normal range of BA (15–35 $m^2\ ha^{-1}$) for the corrected model (Fig. 6). In contrast, for the uncorrected model the change of the same BA range was approximately 2 m.

For the uncorrected model fit to only loblolly pine (Table 3), BA was a significant predictor but DGW was not (p = 0.1834). The open agricultural LULC was different from the base and the Rember-Hornesville and the Fuquay-Blanton-Dothan SAs were greater than the Blanton-Lakeland SA. With error correction, BA and open agricultural LULC were still significant and the results for the SAs were similar to the uncorrected model.

The SEM uncorrected and corrected models derived from the 587 plots were used to predict the SI values of the independent validation data set. A simple linear regression of the predicted versus observed SIs was performed for each model to judge its conformance to a 1:1 line. The adjusted R2 and p-values were similar for both models (Table 4). However, for the uncorrected model the slope of the observed versus predicted SI was less than 1.0 and the intercept was greater than 0, indicating that lower SI values will be overestimated and higher SI values will be underestimated. The slope and intercept of the observed

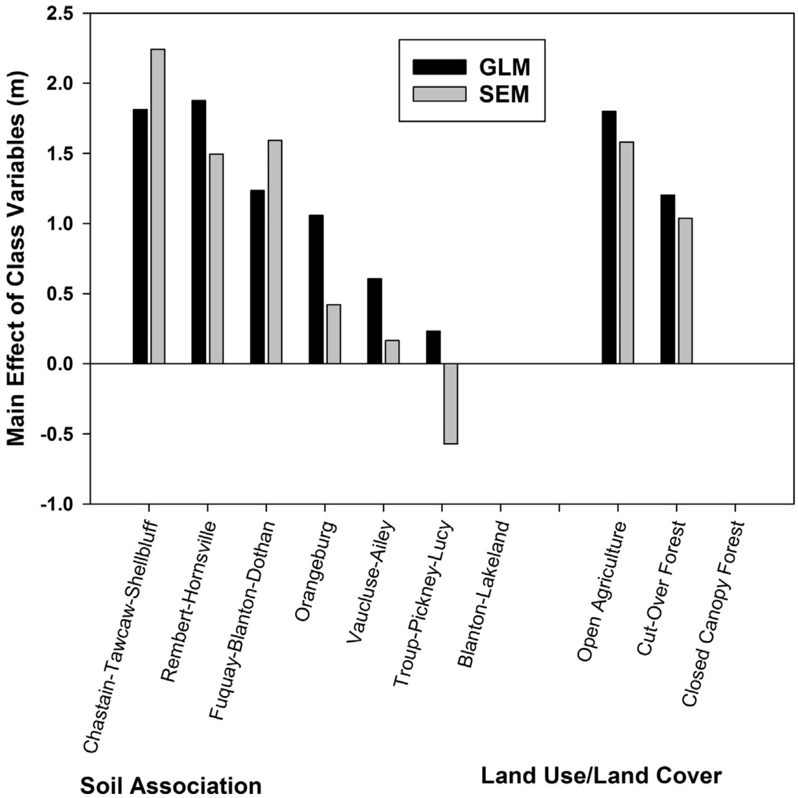

Fig. 4. Main effects of soil association and land use/land cover class on site index (base age 50 years) across all forest groups, basal areas, and depths to groundwater using uncorrected and corrected structural equations, respectively. Blanton-Lakeland and closed canopy forest were the base conditions for soil association and land use/land cover class, respectively.

SI versus predicted SI for the corrected model was substantially different. Although the slope was less than 1.0 (0.82) and the intercept greater than 0 (7.3), the 95% confidence intervals included 1.0 and 0.0, respectively. The other fit statistics, average difference of 2.8 and mean square error of 32.7, showed that although the corrected model reduced the regression attenuation bias, the mean difference and mean square error were larger than the uncorrected model, 2.2 and 14.9, respectively (Table 4). The average difference is a measure of overall bias and is defined as the mean of the difference between the predicted and observed observations. The mean square error is a measure of accuracy which incorporates both bias and variance and is defined as the mean of the difference between the predicted and observed observations

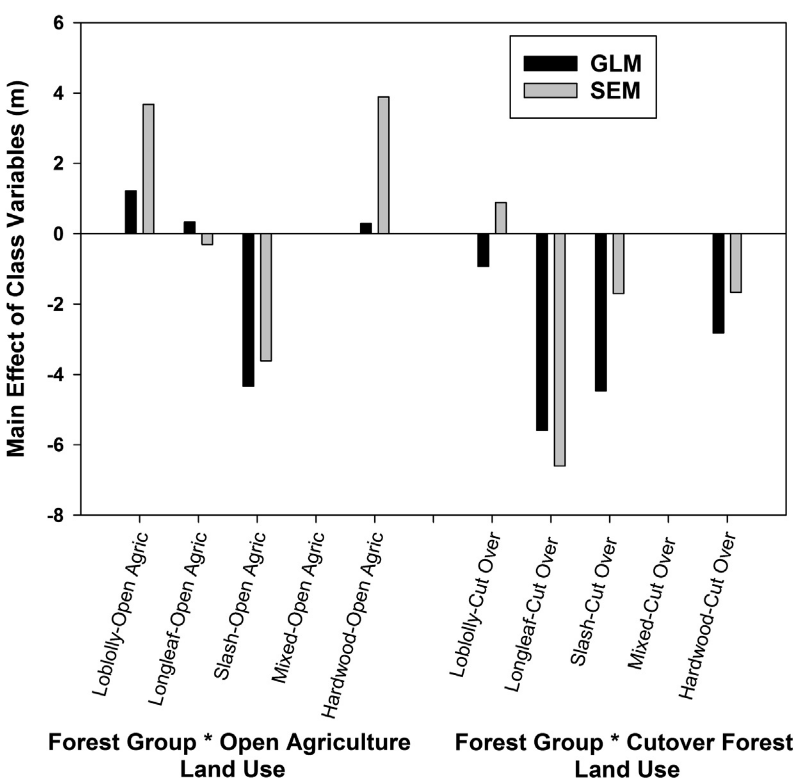

Fig. 5. Interaction effects of forest group and land use-land cover for open agriculture and cutover forest in 1951 on site index (base age 50 years) using uncorrected and corrected structural equations, respectively. Values are across all soil associations, basal areas, and depths to groundwater. Closed canopy forest and mixed pine-hardwood forest were base conditions for land cover/land use and forest group classes, respectively.

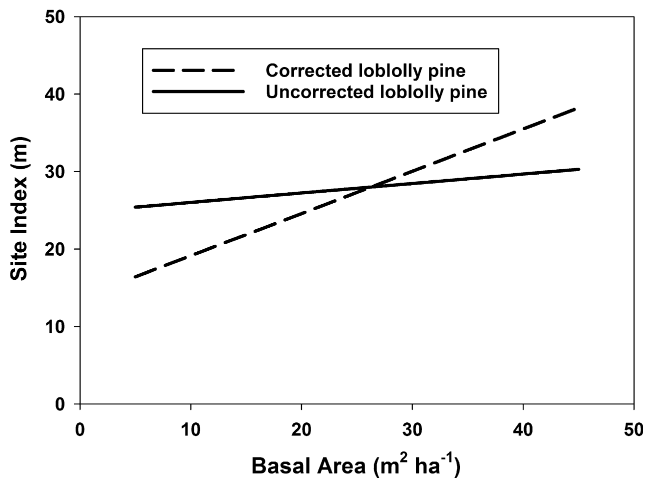

Fig. 6. Predicted site index (m) versus basal area and the latent basal area ($m^2\ ha^{-1}$) for the parsimonious uncorrected and corrected structural equations, respectively, for loblolly pine in the closed canopy land use-land cover category and the Fuquay-Blanton-Dothan soil association. Non-significant effects were removed from the models in Table 2 to create the parsimonious models.

squared. For both models the average difference in SI between the predicted and observed SI showed that the 2010 validation population was over-predicted. Although the 95% confidence interval for the corrected model included 1.0 for the slope and 0 for the intercept, indicating non-significance from a 1:1 line, this could be attributed to its larger variance and wider confidence intervals than the uncorrected model. Thus, there is a trade-off between regression attenuation reduction and the magnitude of bias and accuracy. Although the corrected model removed much of the systematic bias (regression attenuation) that occurred for the uncorrected model at the lower and upper tails of the SI distribution, its overall bias was greater and accuracy was less for this validation data set.

The predicted SI across the northeastern strata of the SRS demonstrates the wide variation in predicted SI (Fig.7). The corrected model clearly identifies the low SI areas of 14–20 m associated with longleaf pines planted on cut-over lands on the Blanton-Lakeland SA. Clusters of high SI are also evident. These are almost all loblolly pine stands plant on former agricultural lands on the Troup-Pickney Lucy SA.

4. Discussion

Attempts to integrate soil taxonomic classification at the soil series level and general topographic features to predict productivity for southern USA pine species have not been successful in the past, except when soils units vary in the extreme (Carmean, 1975). These results have led to attempts to elucidate important chemical and physical properties of soils, which are rarely mapped on non-industrial lands (Schoenholtz et al., 2000). We were somewhat successful by utilizing soil mapping units that were aggregations of related soil series in the form of soil associations created by the NRCS and we had sufficient information on other variables to obtain parameter estimates for those units. The SA parameter reflects that more productive SAs, as indicated by SI, have greater organic content, clay content, or shallower sand over clay layers than less productive soils. These SAs have properties consistent with soil nutrient and water availability variables identified as directly related to SI from other studies in the region (Morris and Campbell, 1991).

High stem densities can have a negative impact on tree height growth in plantations of many conifer species including southern pines at older ages (Lee and Lenhart, 1998; Zhao et al., 2011). Studies designed to construct SI curves generally collect height-age measurements of dominant and co-dominant trees in stands that are well stocked based on local standards. Because most of the SRS stands were thinned periodically beginning at a young age, the stands sampled were in conditions with average BA ~ 25 $m^2\ ha^{-1}$, which is the mid-range for BA in even-aged southern pines and well below self-thinning levels. Although we attempted to constrain SI asymptotically as BA increased by using transformations on BA to reflect empirical evidence that the effect should plateau, none of the transformations substantially improved the models. The square-root of BA gave a similar fit to the BA vs. SI data as no transformation, but transformations of independent variables used in measurement error correction is not preferred unless there is strong evidence of the need to stabilize the variance (Carroll et al., 2006).

We initially anticipated a negative relationship between SI and high

Table 3
Loblolly pine site index model parameters, standard errors, p-values and model fit statistics using structural equation modeling (SEM) with and without basal area and depth to groundwater measurement error correction. Parameter p-values represent the probability that the parameter estimate is significantly different than zero. Main effect p-values are for the chi-square test of the combined class or dummy variables.

N = 255 plots	Without error correction			With error correction		
Variable	Parameter value	Std. error	P value	Parameter value	Std. error	P value
Intercept	22.5210	1.3891	< 0.0001	8.5112	5.7143	0.1364
Basal area ($m^2\ ha^{-1}$)	0.1587	0.0268	< 0.0001	0.6349	0.1941	0.0011
Depth to Groundwater (m)	−0.1362	0.1024	0.1834	0.0018	0.1017	0.9860
Land Use Land Cover	Main effect p-value < 0.0001			Main effect p-value < 0.0001		
Open Agriculture	2.9834	1.0956	0.0065	5.2590	1.9223	0.0062
Closed Canopy Forest	0.0000	–	–	0.0000	–	–
Cut-Over Forest	0.2837	1.0690	0.7907	1.9285	1.7647	0.2745
Soil Association	Main effect p-value = 0.1368			Main effect p-value = 0.2774		
Rembert-Hornsville	2.2204	1.1497	0.0535	2.4045	1.6879	0.1543
Blanton-Lakeland	0.0000	–	–	0.0000	–	–
Fuquay-Blanton-Dothan	1.6745	0.6664	0.0120	1.8205	0.9992	0.0685
Orangeburg	0.6527	1.5598	0.6756	−1.6869	2.5058	0.5008
Vaucluse-Ailey	1.0941	0.8965	0.2223	0.9334	1.3448	0.4877
Troup-Pickney-Lucy	0.1177	1.1759	0.9202	−0.4116	1.7780	0.8169
Fit Statistics						
Akaike's Information Criteria	130			130		
[a]R^2	0.2407			0.5542		
P-Value	< 0.0001			< 0.0001		

[a] R^2 = (1 − (Error Variance SI/Total Variance)).

Table 4
Simple linear regression parameters and fit statistics of the observed vs. the predicted site index for the 89 validation data points collected in 2010. The table includes the results using both the error-corrected and uncorrected structural equation models. The corrected model results are for the final version with depth to groundwater and the interaction with forest groups removed. The p-value is for the overall regression in each case.

Attribute		Uncorrected Model	Corrected Model
Intercept	Parameter	18.3625	7.3473
	Standard error	1.9896	4.1498
	95% Confidence interval	14.4103–22.3155	−0.9009 to 15.5957
Slope	Parameter	0.3714	0.8225
	Standard error	0.0767	0.1600
	95% Confidence interval	0.2189–0.5238	0.5043 to 1.1406
Adj. R^2		0.2083	0.2240
p-value		< 0.0001	< 0.0001
Average difference[a]		2.2	2.8
Mean square error[b]		14.9	32.7

[a] *Average difference* $= \frac{1}{n}\sum_{i=1}^{n}(observed-predicted)$.

[b] *Mean square error* $= \frac{1}{n}\sum_{i=1}^{n}(observed-predicted)^2$.

stocking levels resulting from height growth suppression, but we did not expect to find a positive relationship between increasing BA and SI that is evident in the results. Although SI has a positive effect on volume growth because of increased height growth, research has shown that SI does not have a large effect on BA growth per se in older stands typical of our study (Pszwaro et al., 2016; Quicke et al., 1994), except as it influences mortality. The BA of our stands is strongly influenced by the timing of last thinning or partial cutting. At SRS management prescribed planting density, timing of thinning and residual BA levels following thinning are not linked to SI. The BA is more affected by stand age than SI and therefore in the context of our SEM model we treat BA as an exogenous variable. We believe that the positive relationship below about 30 $m^2\,ha^{-1}$ is a true biological effect rather than an artifact of selective removal of dominant trees. Low density research plantings are uncommon, but average tree heights increased ~1.5 m with planting density from 250 to 1500 trees per ha in a Georgia study with loblolly pine at age 14 that was un-thinned (Pienaar et al., 1997). Heights peaked and then declined at higher densities. Thinning southern pines has also been shown to cause a transient but substantial reduction in height growth (Gyawali and Burkhart, 2015; Peterson et al., 1997). There is a physiological basis for the latter effect in terms of transient increases in moisture stress, whether a result of an increase in transpiration losses, a decrease water uptake from root damage during logging or increase in root disease (Peterson et al., 1997).

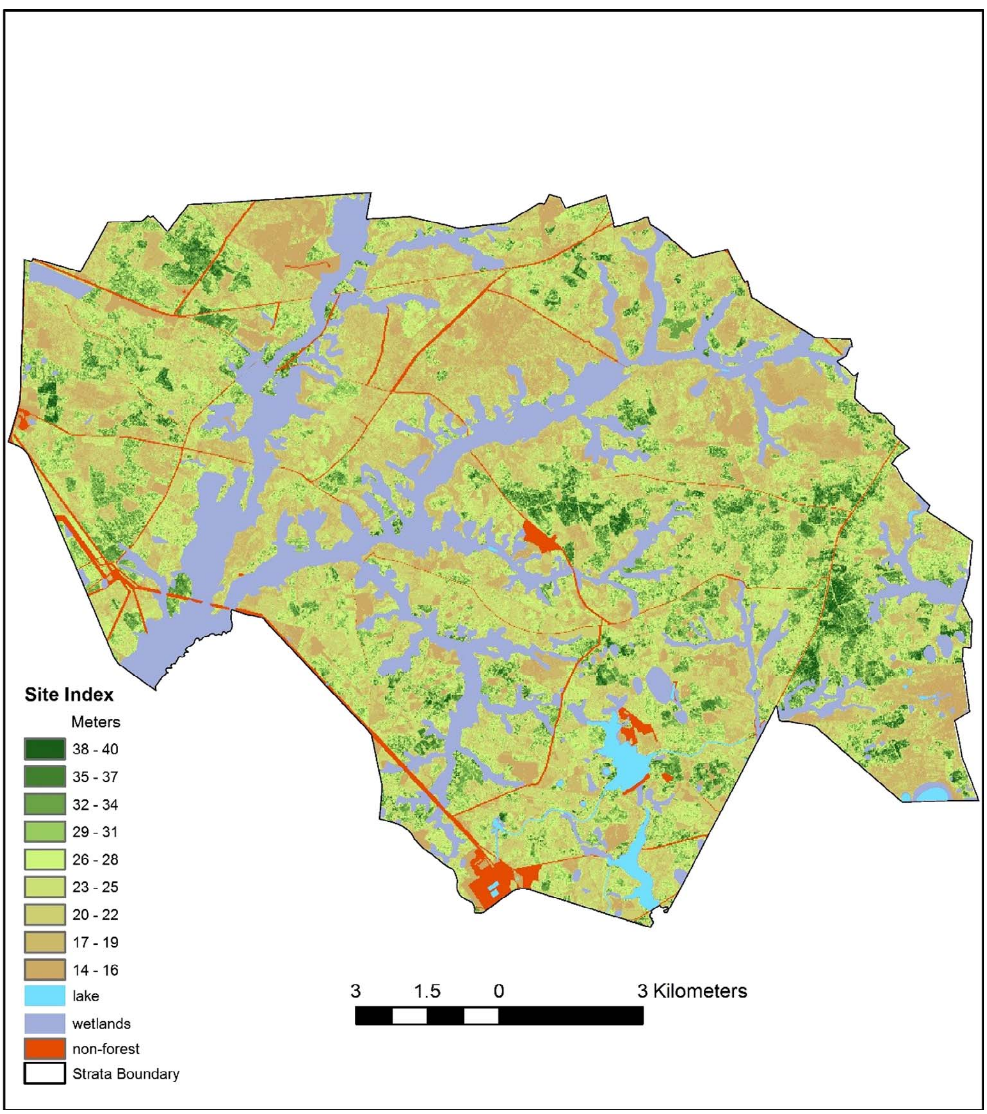

Fig. 7. Continuous cartographic map of Site Index for the upland managed forests of the northeast section of the Savannah River Site based on the error corrected parsimonious model.

The strong positive effect of open agricultural LULC or "old-field" conditions on productivity is well established in young slash, longleaf and loblolly pine plantations (Boyer, 1983). A major result of our study is that the old-field effect can be detected in much older stands than has been previously documented. The effect is very evident in the cartographic map of SI (Fig.7). The detection of these effects may result from cumulative height gains during early development that were maintained rather than continued incremental height growth gains. We know that when the old fields on SRS were planted, they were dominated by grasses (Kilgo and Blake, 2005). Planting furrows were created on open agricultural sites with a fire-plow unit that temporarily reduced grass competition. Studies at SRS showed that the old fields also had higher soil phosphorus levels from prior crop fertilization which can sometimes be limiting to tree growth (Bizzari et al., 2015). The strong interaction between the FTGRPS and the LULC conditions is consistent with general experience. Because of lower initial height growth rates, longleaf pine is more susceptible to growth suppression from competitors, particularly the many woody plants and hardwood trees in southeastern US forests. Although we found no significant main effects for FTGRPs, other SRS experimental studies have shown that loblolly pine will grow substantially larger in height than longleaf pines on intensively prepared sites over a wide range of soils found in the current study (Cram et al., 2010). In part, the lack of FTGRP main effects may be a result of the use of age at DBH, which eliminates the addition of years since establishment that typically is a much larger value for some species like longleaf pine (Carmean et al., 1989).

The modeling results demonstrate that it is possible to create a reasonably reliable predictive model of site productivity from mapped variables where climate variation is inconsequential and where intensive silvicultural activities are limited. There was substantial unexplained variability in the predicted vs observed values for the validation comparison, but we would not expect very precise estimates for point predictions on the landscape and the comparisons are in line with other studies (Aertsen et al., 2010). The important management application is the variation of the mean prediction for SI over management units of 1–10 ha or more, which is substantially larger than the inventory prism point observations. For instance, given the standard error of a SI point prediction, using the model to predict the mean SI over n points over a large landscape as is done in practice, the standard error of the mean SI prediction would be reduced by multiplying by the reciprocal of the square root of n. Thus, using 4, 8, and 16 points, the standard error of the mean SI prediction would be 0.50, 0.35, and 0.25 of the predicted single point estimate, respectively. Thus, as the landscape becomes larger and the number of point estimates increases, the standard error would diminish until it reached a stable plateau.

The model over-predicted mean SI in the validation data set. This over-prediction could be a statistical artifact or real. If real, it implies that average SI declined in the 10-year interval between inventories or that the model parameters have changed. A severe ice storm occurred in January 2004 and investigation of the subsequent damage showed that tall loblolly pines were frequently damaged by ice in terms of broken tops (Aubrey et al., 2007). The effect on total height was confirmed for both loblolly and longleaf pines following a severe ice storm in February 2014 (Bragg, 2016). The ice damage could account for the difference observed. Alternatively if the parameter representing the effects of BA is age dependent, i.e. it increases with age, then the decline could be explained at least partially by age. However there is only a seven year mean age difference between the two inventory SI sample plots (Table 1). Changes in measured SI in longleaf pine over many decades in naturally regenerated stands at the same locations over multiple rotations have been reported (Boyer, 2001). These results suggest that the model provides a reference baseline, but SI parameters may not be stable even in stands with few or any intensive silvicutural inputs.

The results show that prior land use and current stocking conditions have a major impact on SI for the various forest species. The DGW conditions may also be important but we were unable to determine its effect given the measurement error. A major limitation to extending these models to predict productivity elsewhere is the limited availability of BA, LULC and DGW as continuous mapped feature space. Only FTGRPs and SAs are typically available across non-industrial and other governmental landownerships or can be estimated from remote sensing observations. Prior land use conditions were mapped as part of a special project at the SRS to assess environmental impacts. It can be done by other landowners and agencies. This study highlights the value of that information even 50-years later. Stem densities, BA and heights can be precisely obtained for forest stands at 20 m × 20 m scale from LiDAR. Although the 2009 LiDAR project that provided spatially explicit forest inventory metrics and topographic information is the only documented large scale operations project in the region, this technology is now becoming more widely adopted as costs have dropped (Reutebuch and McGaughey, 2012). Sufficient groundwater wells were installed in the 1980–2000 period to manage and remediate groundwater contamination from facilities operations. Because of the critical importance of groundwater, new mapping approaches with increased spatial precision are becoming available (Maxwell et al., 2015).

Although developing relationships between mapped variables and SI obtained from systematic inventories is practical, the approach has inherent limitations. The sampling intensity of our plots was ten times that of the regional forest inventory and analysis plots (Bechtold and Patterson, 2005) for a similar area. These limitations can be largely overcome by linking LiDAR to precise geo-spatially referenced calibration plots and to stand and land management layers, particularly establishment age and treatment history (Gatziolis, 2007). This approach will be applied in the next SRS inventory. In the current study the 587 sample points in the 2000 inventory were uniformly distributed spatially and appeared to reflect the landscape in terms of dominant FTGRP, SAs, DGW and land-use conditions (Table 1) (Kilgo and Blake, 2005). However, despite the large sample size, not all combinations of categorical variables which existed on the landscape were represented. No slash or longleaf pine stands were sampled under closed canopy forest LULC. For other variable combinations, few observations existed, and this also reduced the power of the tests for significance for their effects. The variation in SI, BA and age covered a wide range of conditions. The DGW values were characteristic of the Upper Coastal Plain hydrogeological conditions in the southeastern USA, but some areas with extreme DGW (> 30 m) as measured by wells were not captured in the inventory. The mean and distribution of the 89 validation plots obtained from the 2010 inventory were comparable to the relative distribution of plots from the 2000 inventory with respect to SA, LULC and FTGRP, with the exception of the hardwoods FTGRP category which was dropped from the analysis. The SI tree ages were slightly greater in 2010 as might be expected due to the intervening decade.

Regression attenuation bias resulting from measurement error of the independent variables may be more common than recognized (Sabatia and Burkhart, 2014). The problem has been known for more than 100 years, however most of the applications have been in the medical, economic and social science fields where potential bias in key parameters can have serious consequences (Carroll et al., 2006). Depending upon the application, the bias may not be important, but it can clearly effect the parameter estimates. The measurement errors adjustment clearly changed the apparent effect of DGW. Others have also demonstrated that the choice of the modeling approach can determine which variables are selected (Aertsen et al., 2010). Where our application is primarily to map the SI across the landscape and establish a spatially explicit estimate of SI, the attenuation bias is important. We were able to demonstrate that standard statistical methods for estimating the errors and incorporating them within a SEM framework substantially reduced the over-prediction of low SI conditions and under-prediction of high SI conditions. The R^2 value was improved because the corrected model assigns a portion of the measurement error variance to the independent variables leaving a smaller residual mean square error for the model fit. The statistical cost for the bias correction was the strong tendency for the variance in the model parameters to be inflated which made detection of variable effects more difficult.

5. Conclusions

Mapped spatial variables can be related to SI and provide a useful baseline for predicting growth, carbon sequestration, habitat suitability, and selection of species with limitations. Even on a landscape with low intensity management, the silvicultural impacts on SI can dominate native productive capacity and confound the ability to detect climate effects and atmospheric deposition (Boyer, 2001; Jiang et al., 2015; Pretzsch et al., 2014). We found that soil associations, combined with past landuse and species selection coupled with current management that affected basal area were capable predictors of site index as an indicator of productivity. The legacy of prior land use on SI of stands older than 20-years has not been demonstrated previously. Because it is likely that the LULC, BA and FTGRP parameters will change over time, the model parameters are not likely invariant. An increase or decrease in site preparation, planting densities, thinning strategies, burning, genetic improvements or fertilization may have impacts that far exceed other environmental factors. If the goal is to detect changes in productive potential indexes, detailed tracking and mapping of the extent of these management treatments are required over long periods as well as an understanding of the sample measurement or classification errors. Application of LiDAR coupled forest inventory can substantially increase the precision of stand metrics at very small scales that can enable landowners and agencies to focus on improving the quality of soil, climatic and stand treatment information.

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