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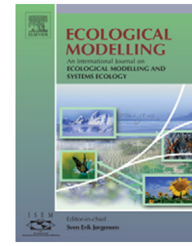

Using the FORE-SCE model to project land-cover change in the southeastern United States

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ABSTRACT

A wide variety of ecological applications require spatially explicit current and projected land-use and land-cover data. The southeastern United States has experienced massive land-use change since European settlement and continues to experience extremely high rates of forest cutting, significant urban development, and changes in agricultural land use. Forest-cover patterns and structure are projected to change dramatically in the southeastern United States in the next 50 years due to population growth and demand for wood products [Wear, D.N., Greis, J.G. (Eds.), 2002. Southern Forest Resource Assessment. General Technical Report SRS-53. U.S. Department of Agriculture, Forest Service, Southern Research Station, Asheville, NC, 635 pp]. Along with our climate partners, we are examining the potential effects of southeastern U.S. land-cover change on regional climate. The U.S. Geological Survey (USGS) Land Cover Trends project is analyzing contemporary (1973–2000) land-cover change in the conterminous United States, providing ecoregion-by-ecoregion estimates of the rates of change, descriptive transition matrices, and changes in landscape metrics. The FORecasting SCEnarios of future land-cover (FORE-SCE) model used Land Cover Trends data and theoretical, statistical, and deterministic modeling techniques to project future land-cover change through 2050 for the southeastern United States. Prescriptions for future proportions of land cover for this application were provided by ecoregion-based extrapolations of historical change. Logistic regression was used to develop relationships between suspected drivers of land-cover change and land cover, resulting in the development of probability-of-occurrence surfaces for each unique land-cover type. Forest stand age was initially established with Forest Inventory and Analysis (FIA) data and tracked through model iterations. The spatial allocation procedure placed patches of new land cover on the landscape until the scenario prescriptions were met, using measured Land Cover Trends data to guide patch characteristics and the probability surfaces to guide placement. The approach provides an efficient method for extrapolating historical land-cover trends and is amenable to the incorporation of more detailed and focused studies for the establishment of scenario prescriptions.

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1. Introduction

The landscape of the southeastern United States has historically been marked by massive change in land use and land cover. Early European settlers described vast open forests and savannahs, vegetated with southern oaks, pines, and hickories (Delcourt et al., 1993; Carroll et al., 2002), a landscape partially shaped by Native Americans use of fire (Hudson, 1982; Williams and Johnson, 1992; Stanturf et al., 2002). By the late 19th century, agricultural expansion and an expanding timber industry caused the depletion of native forest land. By the 1920s, so much land had been logged that timber companies began to close mills and move to the relatively untouched forests of the Pacific Northwest (Owen, 2002), and much of the landscape in the Southeast was seriously degraded (Wear and Greis, 2002). The declining ability of the landscape to support agriculture, along with the invasion of the boll weevil, resulted in large-scale agricultural abandonment, with the number of farms in the region decreasing 80% between 1930 and 1997 (Burkett et al., 2000).

By the 1950s and 1960s, the timber industry was rebounding, aided by the establishment of plantation cultivation of a handful of southern pine species. Southern states produce most of America's industrial wood output, and their share has grown steadily since the 1960s (Prestemon and Abt, 2002). Planted and cultivated pine, largely absent in the South in 1950, represented nearly half of all Southern forest cover by 2000 (Conner and Hartsell, 2002). Climate favorable to rapid growth for loblolly pine and other Southern pine species permits harvest cycles as short as 20–25 years (Gresham, 2002), resulting in a continually changing forest structure.

The climate of the southeastern United States, characterized by long, hot growing seasons, is extremely favorable to supporting today's vast pine plantations, but weather disturbances such as microbursts, tornadoes, and hurricanes can have major impacts on land cover and vegetation structure (Peterson, 2000). Conversely, vegetation and land-cover change in the Southeast result in feedbacks to regional climate and weather. Land-cover change affects regional climate through changes in surface energy, water balances, and the division of energy into sensible and latent heat (Pielke et al., 2002; Kalnay and Cai, 2003; Snyder et al., 2004; Foley et al., 2005). Pielke et al. (2007) suggest that changes in temperate forests result in regional precipitation change, with general increases in precipitation in areas that have been reforested. Jackson et al. (2005) indicated that establishing tree plantations significantly alters hydrologic cycles. Pielke et al. (1999) showed that widespread conversion of natural vegetation to urban and agricultural lands in south Florida has resulted in significant changes in precipitation and temperature. Anantharaj et al. (2006) showed changes in patterns of rainfall in Louisiana based on differing land-cover prescriptions.

Forest-cover patterns and structure are projected to change dramatically in the southeastern United States in the next 50 years due to population growth and demand for wood products (Wear and Greis, 2002). Accompanying the significant land-cover change will likely be shifts in regional climate and weather patterns. The overarching goal of this research is to examine the extent to which future changes to regional land-use and land-cover characteristics affect regional weather and climate variability. The FORecasting SCEnarios of future land-cover (FORE-SCE) model was initially developed to provide regional land-cover projections for multiple scenarios in the Western Great Plains (Sohl et al., 2007). The Western Great Plains work focused on scenarios of agricultural expansion or decline in a landscape quite different from the southeastern United States. Forest change (in both cover and structure) is the dominant form of land surface change in the Southeast, requiring substantial modifications to the Western Great Plains modeling framework. This manuscript focuses on using the FORE-SCE modeling environment to provide future regional landscapes in the southeastern United States in support of the analysis of impacts on climate.

2. Background

The study area covers about 1.2 million km^2 of the southeastern United States, including all or portions of 11 U.S. States, covering 20 different EPA Level III ecoregions (Omernik, 1987) (Fig. 1). Projected land-cover products were required to serve as input to Colorado State University Regional Atmospheric Modeling System (RAMS) and the General Energy and Mass Transfer Model (GEMTM) (Eastman et al., 2001; Chen and Coughenour, 1994). Land-cover products required thematic detail roughly analogous to the 1992 NLCD classification scheme (Vogelmann et al., 2001) (Table 1). Required spatial resolutions for RAMS-GEMTM modeling were at a minimum of 1-km grid resolution. However, data input for the climate modeling requires cell-based proportions of change (e.g., 25% forest, 25% urban, 50% agriculture for a particular cell). To facilitate aggregation of land-cover proportions to the larger 1-km grid cell resolution, discrete pixel-based land-cover maps for the study area were required at a 250-m spatial resolution. Given the dynamic nature of forest use in the southeastern United States and the resultant impacts of different forest age structures on biophysical parameters

Table 1 – Mapped land cover classes

1	Open water
2	Urban/developed
3	Naturally barren
4	Mining/quarry
5	Transitional barren
6	Deciduous forest
7	Mixed forest
8	Evergreen forest
9	Shrubland
10	Woody cultivated
11	Natural grassland
12	Hay/pasture
13	Row crop
14	Small grains
15	Woody wetland
16	Herbaceous wetland

Land cover classes mapped and projected in the southeastern United States study area.

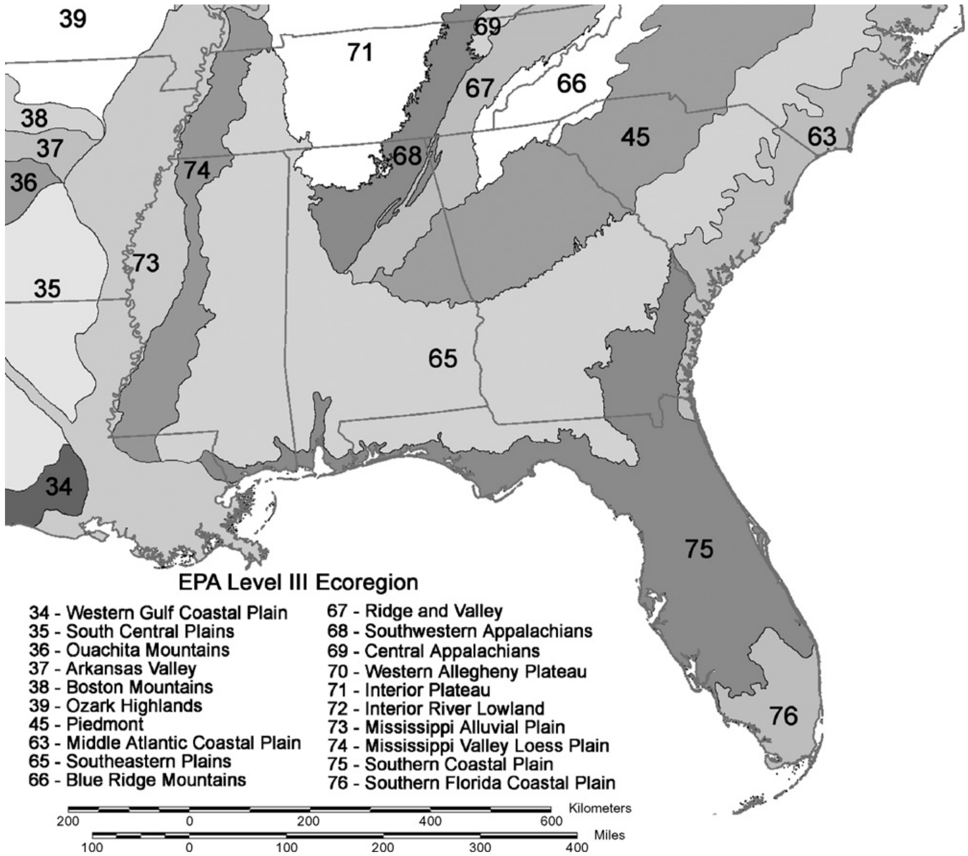

Fig. 1 – Study area: the southeastern United States. The study area encompasses about 1.2 million km^2, covering 11 states and 20 different EPA Level III ecoregions (Omernik, 1987).

important to RAMS-GEMTM climate model results, basic information on forest age was required, along with land-cover data type.

There have been a number of prior efforts to forecast land-use and land-cover change in the southeastern United States. Wear and Bolstad (1998) developed a forecasting model for land-use change in four small study areas in the southern Appalachians, modeling nonforest and forest with various building densities. Pearson et al. (1999) predicted landscape change for four land-cover classes in a small (103,635 ha) area in the Little Tennessee River Basin. Hardie et al. (2000) modeled land use for 1400+ counties across much of the southern United States, providing county-level proportions of three classes (farm, forest, and urban). Similarly, Wear et al. (2004) built on Hardie's work to forecast the effects of population and economic growth on the distribution of interior forest habitat in the South, also modeling county-level changes. Compared to these other studies, our research activities modeling land-cover change in the southeastern United States are more regional in geographic scope and are characterized by much finer spatial and thematic resolution.

There have also been many activities focused on directly modeling forest growth and productivity in the study area. The PnET-II model has been used extensively to model future changes in forest productivity [net primary productivity (NPP), Leaf Area Index (LAI)] (McNulty et al., 1996; Sun et al., 2000; Liang et al., 2002). McNulty et al. (2000) attempted to link PnET-II with forest biogeography models (predicting species composition) and economic models of forest management in Southern timber markets. The Forest Landscape Disturbance and Succession (LANDIS) model has been applied in a wide variety of forest settings, modeling forest succession and dispersal, as well as disturbance from fire, wind, harvesting, and biological agents (Mladenoff et al., 1996). LANDIS applications typically use high to moderate resolutions (10 m to 1 km) and 50- to 2000-year projections operating at 10-year time steps over geographic areas ranging from 10 to 100,000 km^2. The resultant projections for harvest estimates, species composition, and forest productivity have typically been produced at the county level. Directly modeling forest productivity through models such as PnET-II and LANDIS can potentially provide detailed projections on forest biophysical parameters required by RAMS-GEMTM modeling. However, they typically have not been applied at both the required spatial resolution and geographic coverage required by this application, can require exceptionally detailed harvest prescriptions and other model parameterization, and do not address other forms of land-cover change.

3. Methods

We used a significantly modified version of the FORE-SCE model to project land-cover change in the southeastern United

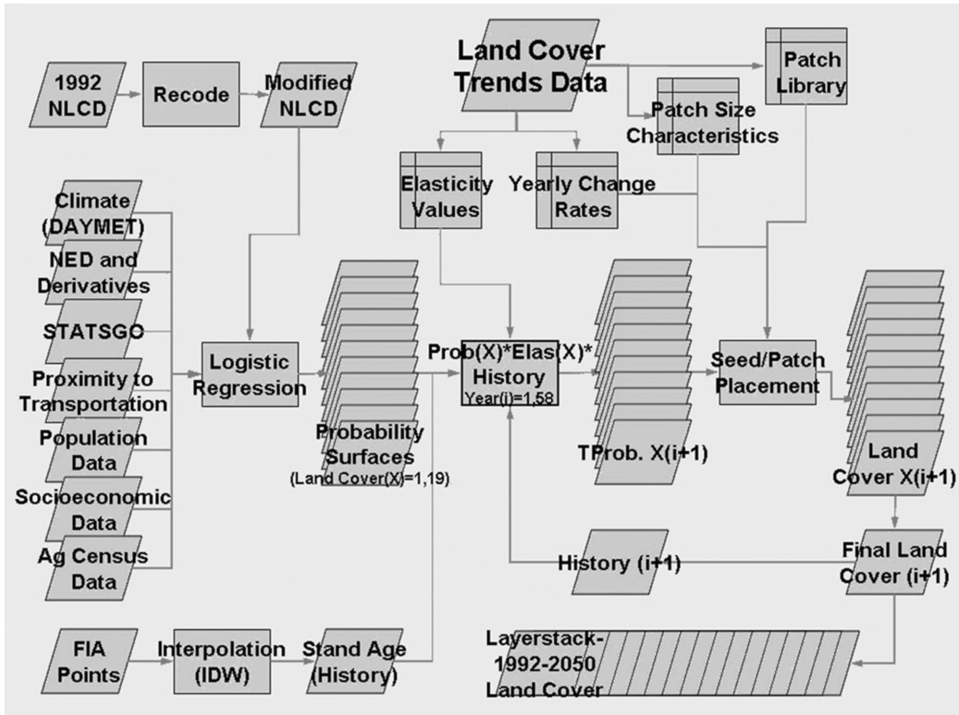

Fig. 2 – FORE-SCE structure: basic FORE-SCE structure. FORE-SCE relies heavily on Land Cover Trends data for model parameterization. Land-cover modeling begins with a modified 1992 NLCD (Vogelmann et al., 2001) data layer. Logistic regression is used to develop probability-of-occurrence surfaces for each land-cover type being mapped. Individual patches of new land cover are placed on the landscape in an annual iteration until the scenario prescriptions have been met. The process continues with yearly iterations, with a history variable tracking age classes for forest and other classes.

States from 1992 to 2050. The FORE-SCE application in the Western Great Plains (Sohl et al., 2007) focused on shifts in agricultural use for multiple scenarios from 1992 to 2020. This FORE-SCE application in the southeastern United States focuses primarily on the shifting distribution and structure of forest lands, with urban development and agricultural use secondary stories. Specifically, to facilitate parameterization of land-cover characteristics specific to various forest structures, this application required the modeling of changes in both thematic land-cover type and forest age structure. We are once again starting with the 1992 land cover, using 1992 National Land Cover Data (NLCD) (Vogelmann et al., 2001) as our starting landscape, but we are projecting to 2050 instead of 2020. Use of the 1992 data as our starting point allows us some measure of model calibration and performance using U.S. Geological Survey (USGS) Land Cover Trends data (Loveland et al., 2002), as discussed in Section 4.

The FORE-SCE modeling approach to date has focused on the spatial allocation of change. Given our desire to analyze the potential effects of different landscape configurations on climate and weather variability, absolute prediction played a secondary role to the ability to analyze how different realistic landscapes potentially affect weather and climate. Scenarios, therefore, have largely been defined as either extrapolations of historical land-cover change patterns or broad-level modifications of extrapolated patterns. Extensive econometric modeling, or other approaches defining "demand" for specific land-cover types, is beyond the scope of this current application, although as noted below, work has begun on a separate demand module for subsequent applications.

Fig. 2 outlines the basic structure of FORE-SCE. A land-cover scenario defines the total amount of change for each mapped land-cover type, while historical patch characteristics for individual land-cover transition types guide the number and size of required patches to fulfill the total change prescription. Logistic regression is used to define relationships between historical land-use and the various ancillary data sources that drive it. Probability-of-occurrence surfaces derived from logistic regression guide the placement of change patches. Individual patches of new land covers are placed on the landscape until the change prescription for the study area is achieved.

Due to time considerations and model processing times, the initial FORE-SCE application in the Western Great Plains directly modeled 1992–2020 land-cover change in one application of change polygons. To adequately model changes in forest age structure in the southeastern United States, we have modified FORE-SCE to run iteratively, year-by-year, using an annual prescription of change applied from 1992 to 2050. A closer examination of model processes and improvements incorporated in this application are discussed below.

3.1. *Scenario development and parameterization*

The scenario described in this paper was an extrapolation of USGS Land Cover Trends project results (Loveland et al., 2002)

for the 20 EPA Level III ecoregions (Omernik, 1987) in the study area. The Land Cover Trends project is analyzing land-cover change across the conterminous United States using a historical archive of 1973–2000 Landsat data. A sampling approach and five mapped land-cover dates (1973, 1980, 1986, 1992, and 2000) provide estimates of land-cover change for each of the 84 EPA Level III ecoregions. Land Cover Trends results can be used to examine trends in individual land covers (e.g., increases or decreases in developed land, agriculture, forest, etc.), quantification and subsequent likelihood of specific transition types (e.g., forest land lost to development, agricultural land abandonment, reversion to forest, etc.), and changes in various landscape metrics (e.g., decreases in average patch size for a given land cover, increases in fragmentation, etc.).

For the scenario described in this paper, we extrapolated Land Cover Trends results from the 1992 to 2000 time period, providing ecoregion-by-ecoregion, annual "prescriptions" for key variables required by FORE-SCE. Ecoregions provide a strong geographic framework for land-cover change studies, as land-cover conversions have been found to have unique characteristics within ecoregions (Griffith et al., 2003). The Land Cover Trends project allowed us to capitalize on these unique characteristics. The annual prescription relied on Land Cover Trends data to provide information on the rates of change for individual land cover types, likelihood of specific land-cover transitions, and basic characteristics of patch size. Overall prescribed annual change per class was extrapolated from Land Cover Trends change rates. For a given land cover, all land-cover transitions changing to that class were summed from the Land Cover Trends 1992–2000 time period, resulting in an overall tally of land transitioning to that class. This value was then normalized to an annual rate of gain for that particular land-cover type, a value which was uniquely determined for each ecoregion in the study area depending upon regional Land Cover Trends results.

For the FORE-SCE patch-based spatial allocation of change, that annual rate of change must be converted to the required annual number of new patches for each land-cover type. Mean patch size for a given land-cover type was used in conjunction with the prescription for annual area changed to determine the number of new patches required annually for that land-cover type. FRAGSTATS (McGarigal et al., 2002) was used to characterize mean patch size and standard deviation for changed Land Cover Trends patches in the 1992–2000 time period. During subsequent spatial allocation procedures, patch size for new patches of each land-cover type were modeled based on a normal distribution around the Land Cover Trends-measured patch size mean and standard deviation. Dividing the prescription for total area by the mean patch size for a given land-cover type thus provided the number of prescribed patches for each land-cover type for each ecoregion in the study area.

Note that annual patch prescriptions for a given land-cover type were based completely on the amount of land transitioning to that class, as measured by the Land Cover Trends project. A separate parameter within FORE-SCE is used to model what class that land was transitioning from. The CLUE series of models (Veldkamp and Fresco, 1996; Verburg et al., 1999, 2002) uses an 'elasticity' modifier of baseline probability values, a practice we have included within FORE-SCE. Elasticity values range from "0" to "1" at 0.1 increments and were used to modify baseline probability values for subsequent probability surface generation procedures. For all "new" (changed) lands transitioning to a given land-cover type, Land Cover Trends data were used to determine the source land-cover type. Contingency tables from 1992 to 2000 reveal the total changed area for every land-cover type transitioning to the endpoint cover type being modeled. Elasticity values for each possible land-cover transition type were then set from 0 to 1 for that endpoint land cover, based on the relative likelihood of each specific transition type occurring in a given ecoregion.

The final model parameter, in conjunction with probability surfaces constructed in the next step, determined how clumped or dispersed patches of new landscape change are. A partially stochastic patch-placement procedure only allowed placement of a new land-cover patch in areas with a relatively high probability of the new land-cover type occurring. A "clumpiness" parameter determined what portion of the probability surface for a given land-cover type is allowed to change. "Clumpiness" was determined by examining the characteristics of change for a given ecoregion and determining whether change to a given land-cover type tended to occur in spatially clumped patches or was more dispersed across the landscape. "Clumpiness" simply states what portion of the cumulative histogram for a given probability surface is allowed to change. For example, a "clumpiness" value of 10 only allowed change patches to be placed on the highest 10% of probability values for that land-cover type. At this time "clumpiness" was iteratively determined using a qualitative examination of ecoregion characteristics and resultant distributions of change on test model runs. Given the extreme variability in probability surface characteristics between different land-cover types and different ecoregions, it was extremely difficult to quantitatively determine "clumpiness" from an examination of historical Land Cover Trends data, but we continue to examine the possibility for a more rigorous, quantitative approach for modeling patch distribution characteristics.

Rates of change information, patch size characteristics, resultant prescriptions for annual patches of new land cover, elasticity values, and clumpiness values are all analyzed and parameterized separately for each ecoregion in the study area. For proper FORE-SCE parameterization and scenario development, it is vital that Land Cover Trends or other similar historical data be available for assessment at a thematic and spatial scale similar to specified model run parameters.

3.2. *Development of probability surfaces*

FORE-SCE relies on probability-of-occurrence surfaces for each land-cover type to be mapped in a study area. Development of probability surfaces relies on identifying the unique biophysical and socioeconomic drivers related to land-use type at a given location. These drivers, or proxy variables representing them, must be "mappable" at the scale of analysis and available for the entire geographic region. The challenge is to develop a comprehensive understanding of land change that couples biophysical and socioeconomic processes at all relevant scales (Rindfuss et al., 2004). However, a more realistic goal is to capture primary, generalized biophysical and socioeconomic processes at multiple scales (Sohl et al., 2007), with a

realization that perfect representation of all contributing driving forces is impossible. Attempts have been made in the past to establish lists of potential drivers of change (Lambin et al., 2001; Agarwal et al., 2002), but drivers of land-use change for an investigation are unique, based on geographic setting and the spatial, temporal, and thematic scale of analysis (Sohl et al., 2007).

Through literature reviews and statistical investigation, significant time was spent determining which drivers were potentially useful for determining location of individual land-cover types. A wide range of potentially useful biophysical and socioeconomic data sets with appropriate spatial resolution and geographic coverage was compiled (Table 2). Potential drivers of change were noted for each land cover, and stepwise logistic regression was used to identify statistical relationships between drivers of change and each mapped land-cover type. Regression results are then used to produce probability-of-occurrence surfaces for all mapped land-cover types in the study area. Note that for this application, logistic regression and the resultant probability surfaces for each land-cover type were constructed for the entire Southeastern study area, rather than individually for each ecoregion. While we recognize the uniqueness of land-cover characteristics for each ecoregion, it takes significant time to model probability surfaces individually for each of the 20 ecoregions in the study area for each of the land-cover classes mapped. In order to meet project deadlines given project resources, we thus decided to model probability surfaces for each land-cover type for the entire study area. We recognize this decision likely affected local accuracy of probability surfaces in some areas, and would prefer to individually model probabilities for each ecoregion. However, examination of initial results indicated that within-ecoregion relative probabilities within an ecoregion were still quite good using this approach. Because the actual spatial allocation of change within FORE-SCE only depends upon relative, within-ecoregion probabilities, we felt that modeling probability-of-occurrence for the entire study area, while not ideal, still provided adequate within-ecoregion discrimination of likely land-cover distributions.

Robust analyses of land-use patterns are typically better obtained by the analysis of end-term (i.e., current) land use, which has had a long evolutionary history, rather than from short-term land-use change data (de Koning et al., 1998; Hoshino, 2001; Sohl et al., 2007). Therefore, we used endpoint, static 1992 NLCD data as land cover in the logistic regressions, rather than developing probability surfaces based on Land Cover Trends change results. 1992 data were first modified to thematically match the required output land-cover classes in Table 1. A thematically and spatially stratified random sample of 50,000 unique point locations was then selected. A minimum of 1000 points for each mapped land-cover class were selected to ensure adequate representation for each. The random sample was stratified spatially to try to minimize the effects of spatial autocorrelation. Linear regression results will be affected by spatial autocorrelation within any spatially explicit study of land cover and land-cover change (Overmars et al., 2003), resulting in potentially inaccurate parameter estimates and measures of statistical significance (Walsh et al., 1997), but the influence of spatial autocorrelation can be minimized by selecting a spatially stratified random sample of pixels (Verburg et al., 2002). Ecoregions were used as a simple means of coarsely stratifying the sample, with a minimum of 1000 points for each of the 20 ecoregions in the study area, including representation of every mapped land-cover class for every ecoregion (where present). As an additional measure to help account for spatial autocorrelation, X- and Y-coordinate values have been included within the regression models as an independent variable, as suggested by Bailey and Gatrell

Table 2 – Independent variables and data source for logistic regression

Population density (1)—persons per square kilometer
Elevation (2)—elevation in meters
Slope (2)—mean slope per grid cell in degrees
Compound Topographic Index (CTI) (2)—wetness measure calculated as a ratio of catchment area and slope
Distance from city center—zone of influence of urban centers, weighted by city population
Distance from road (3)—distance from any road
Distance from interstate (3)—distance from any federal Interstate highway
Distance from railroad—distance from railroad line
Available water capacity (4)—volume of water available to plants if the soil were at field capacity
Soil depth (4)—soil depth in meters
Soil bedrock (4)—percentage area of each map unit with soil components containing weathered or unweathered bedrock
Crop Capability Index (4)—suitability of soils for supporting crop, with decreasing capability as index value increases
Cooling degree days (5)—1980 to 1997 mean of annual cooling degree days
Daily average temperature (5)—1980 to 1997 mean of daily average temperatures
Growing degree days (5)—1980 to 1997 mean of annual growing degree days
January minimum temperature (5)—1980 to 1997 mean of average January minimum temperatures
July maximum temperature (5) – 1980 to 1997 mean of average July maximum temperatures
Heating degree days (5)—1980 to 1997 mean of annual heating degree days
Frost days (5)—1980 to 1997 mean of annual number of days with frost
Total precipitation (5)—1980 to 1997 mean annual precipitation
Wood employment (6)—2000 county-level location quotient of wood-based employment
Distance from historical coal mining—distance from historical coal mining locations
Distance from historical forest cutting—distance from 1992 NLCD recorded forest cutting activity
XMAP—center X-coordinate for each 250 m pixel
YMAP—center Y-coordinate for each 250 m pixel

(1)—From Bureau of the Census data (Bureau of Census, 1991a, 1991b, 1992)
(2)—From National Elevation Dataset (NED) (U.S. Geological Survey, 1999)
(3)—Watts (2005)
(4)—From STATSGO data (U.S. Department of Agriculture, 1994)
(5)—From DAYMET data (Thornton et al., 1997)
(6)—From 1992 NLCD (Vogelmann et al., 2001)

Ancillary data sets used in logistic regression to develop probability-of-occurrence surfaces for each land cover type in the study area. Each data set was formatted and rasterized to 250 m grid cell resolution.

(1996). These are simple but incomplete measures for dealing with autocorrelation. Given project resource limitations in this application, more in-depth accounting for spatial autocorrelation will be conducted in future FORE-SCE analyses.

Multicollinearity issues are common in regression analyses of land-cover distribution because many of the candidate explanatory factors are very closely related. Kok (2004) simply examined correlation values between pairs of variables and excluded one of two variables if correlation values exceeded a certain threshold. To account for multicollinearity issues, we used expert knowledge and examination of paired variable correlation values to similarly exclude redundant or likely redundant variables from the logistic regressions, an issue which occurred most often with inclusion of multiple climate data variables. We also recognize that logistic regression does not necessarily identify causation for the distribution of the dependent variable (land-cover type), only statistical explanation. Expert knowledge and literature reviews were similarly used to examine the relevance of input independent variables. Variables without likely explanatory power for a given land-cover type were excluded from the analysis.

With consideration of the factors mentioned above, for each land-cover class, the final set of accepted potential explanatory variables was analyzed with stepwise logistic regression. Probability-of-occurrence surfaces were constructed from regression results for each land-use class, with probability value P for each pixel h defined as:

$$P_h = \left\{1 + \exp\left[-\alpha - \sum_{k=1}^{t} \beta_k \chi_{hk}\right]\right\}^{-1}$$

where P_h is the probability for pixel h being a member of the land-use class; α the intercept parameter; β the regression coefficient of predictor variable k; χ the predictor variable k value at pixel h.

Table 3 provides a list of the independent variables selected by the logistic regression procedure for each land-cover class.

3.3. *Modeling forest stand age*

The RAMS-GEMTM model requires multiple biophysical parameters for coupled land–atmosphere modeling, including albedo, leaf-area indices, and vegetation indices. Biophysical parameter data sets are constructed based on the mapped land-cover classes that we provide and typical biophysical characteristics of those classes for a given region. Given the extremely dynamic forest landscape in the southeastern United States, our climate partners desired the ability to track stand age, allowing for unique biophysical parameterization for various classes of mapped stand age and forest type, for each distinct ecoregion. To effectively map forest stand age and to more realistically portray an end-point landscape resulting from years of individual land-cover transitions, FORE-SCE was modified to provide yearly iterative model runs from 1992 to 2050.

A "history" variable was initiated to track forest age through time as FORE-SCE model runs progressed and as clear-cutting and subsequent re-growth occurred. The difficulty was establishing an initial forest age for all forest pixels in the southeastern U.S. study area for the starting 1992 date. We acquired 21,254 Forest Inventory and Analysis (FIA) points, with associated point stand age, for all states within our study area (Fig. 3). We used inverse distance weighted (IDW) interpolation to create a continuous stand age surface from these points. FIA point data varied greatly in density by state. While low densities are expected and are not as much of a problem in primarily agricultural areas (Figs. 1 and 3, Mississippi Alluvial Plain and Interior River Lowlands ecoregions, southern third of Florida, etc.), some heavily forested areas also have low FIA point densities (portions of Missouri, West Virginia, Mississippi, etc.). Watson and Philip (1985) note that IDW application may not properly represent surface conditions if the input point sample is sparse or uneven. However, the FIA-based interpolations were the best quality data for stand age available to us.

The resultant interpolated image was used to initialize stand age for all forest pixels in the beginning 1992 land-cover data set, with pixel-by-pixel age recorded in the "history" layer. With each successive yearly run, "history" is incremented upward by a value of 1 for all forest pixels not changing during that iteration. "New" forest pixels (e.g., areas recently converted to forest, such as agricultural fields converted to pine plantation or forest areas cleared for urban development) are initiated with a history value of 0 as model processing proceeds.

3.4. *Spatial allocation of change*

Once the scenario requirements were set, model parameterization complete, and probability surfaces constructed, the spatial allocation of change was fairly straightforward. The process involved placing individual patches of land cover until the scenario prescription for that land-cover type was met. The number of new patches for a given land-cover type was set by the scenario prescription, specific to ecoregion and land-cover type. Patch sizes were then uniquely assigned to each new patch by approximating the historical distribution of patch sizes for each land-cover type. The historical mean and standard deviation for patch size, as measured by the Land Cover Trends project for a given ecoregion, were used to represent a typical patch-size distribution for each land-cover type, simplified by representing it as a Gaussian distribution. Patch size was then assigned to each seed with the use of a number generator capable of producing a random value within the desired Gaussian distribution. Assigning patch size using this methodology ensured that the mean patch size for all new patches equaled the historical mean for a given ecoregion. Given the method used to generate scenario prescriptions, the prescribed number of patches resulted in the correct representation of total new area for each land-cover type.

In the first FORE-SCE application in the Western Great Plains, the patch placement procedure initially involved the placement of "seed" pixels, placed according to characteristics of the underlying probability-of-occurrence surface. The patch was then "grown" from the seed location to the proper size, using the probability-of-occurrence surface to restrict growth to areas favorable for that land-cover type. While the method was used successfully for that application, it was computationally expensive to grow polygons based on underlying probability surface characteristics. Over 1,000,000 seeds were

Table 3 – Logistic regression results

Ancillary data	Land cover class														
	Open water	Urban/ developed	Natural barren	Mining/ quarry	Transitional barren	Deciduous forest	Mixed forest	Evergreen forest	Woody culti- vated	Natural grass- land	Hay/ pasture	Row crop	Small grains	Woody wetland	Herbaceous wetland
Population density	–	+	–	–	–	–	–	–	–	–	–	–	–	–	–
Elevation	–				–		–		+	+	+		–	–	–
Slope		–	–			+	+		+	–	–	–	–	–	
Compound Topographic Index (CTI)	+	–	–	–	–	–	–	–		–	–		+	+	+
Weighted distance from city center		–	–					+	–	+			–	+	
Distance from road	+	–			–		–	–	–	–	–	–	–		+
Distance from interstate		–	+		+		–					+			
Distance from railroad	+	–		–	–								–		
Soils—available water capacity	–			–						–		+	+		+
Soils—soil depth			–												
Soils—bedrock															
Crop Capability Index	+								–	–	–	–	–	+	+
Cooling degree days	–					–	–	–					+	+	
Daily average temperature							+	+	+	–					
Growing degree days						+				+		–	–		
January minimum temperature		+			–	–		–	–	–		–	–	–	
July maximum temperature					+	+	+			–		+		+	–
Heating degree days		+					–	–		–	–		+		+
Frost days								+	–	+	+	–	–		–
Total precipitation		+	–		+	+	+	+	–	–	+			+	+
Wood employment					+		+	+				–			
Distance from historical coal-mining				–											
Distance from historical forest-cutting					+	–					–	–	–		
XMAP	–	+	–	+	+		–	+	+		–	+	–	+	
YMAP			+	+	–							–	–	–	

The following lists the independent variables used for probability surface construction for each land cover class. Positive sign indicates an increase in probability upon increase in variable value. Negative sign indicates a decrease in probability upon increase in variable value. All variables used were significant at $p < 0.01$.

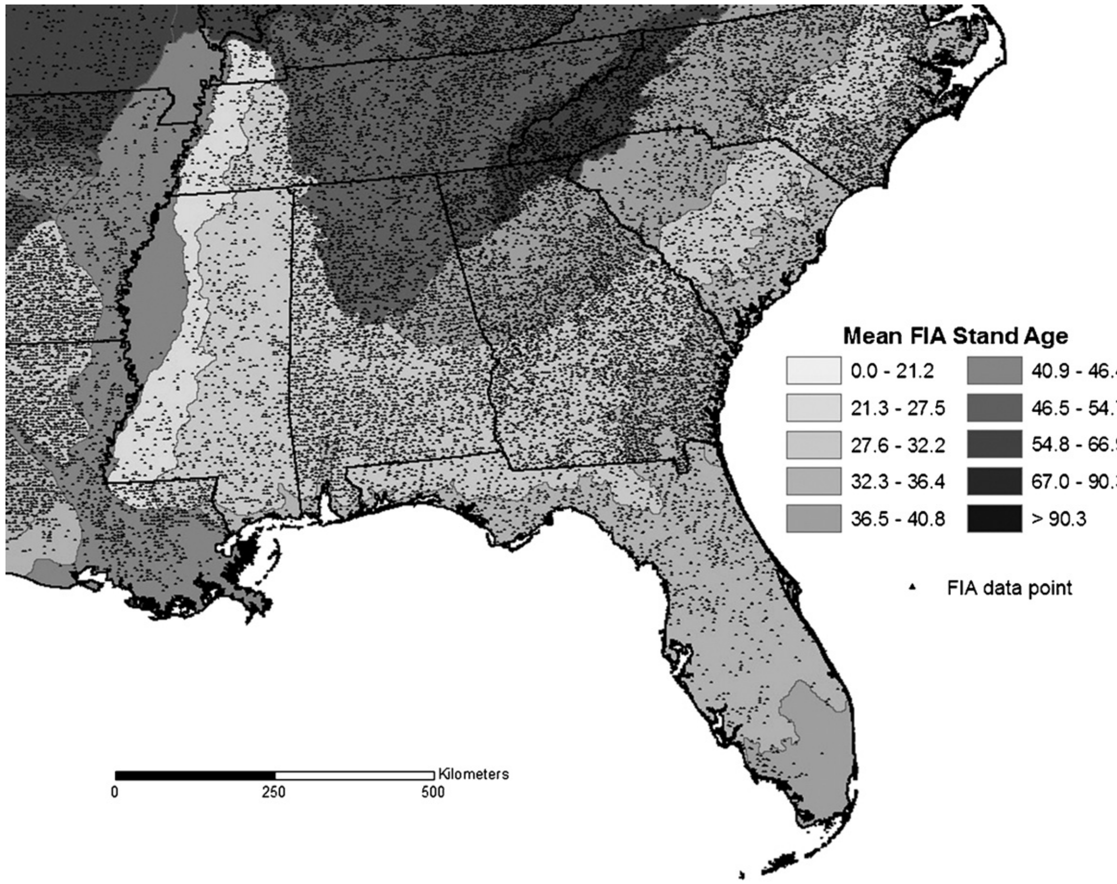

Fig. 3 – FIA data points: 21,254 Forest Inventory and Analysis (FIA) data points in the study area were acquired, and inverse-distance weighted interpolation used to generate a continuous surface of stand age. The underlying shading indicates mean 1992 forest stand age for each ecoregion in the study area.

placed and resultant polygons were grown in the Western Great Plains, resulting in processing times unacceptable and impractical for the southeastern United States work, where 58 individual yearly model iterations were required. For this application, we abandoned the patch-growing procedure and moved to a computationally simple “patch library” approach. For every possible patch size, a library of pre-constructed patch configurations was developed. During the patch placement procedure, patch size was initially determined for a given patch using the method discussed previously, and patch shape/configuration was determined by random selection of a shape from the patch library for that patch size. The process of patch library construction for this application was made considerably easier by the characteristically small patches of change historically mapped in the Southeast at this scale of mapping (250-m cells). With mean patch sizes for most landcover types, across most ecoregions, typically ranging from only one to four 250-m pixels, only a few patch configurations were possible, resulting in an easily constructed library of potential patches. Additional implications of using the patch library approach are discussed in the conclusion section.

Patch placement on the landscape is dependent upon the combined characteristics of the underlying baseline probability surface (generated from logistic regression results) and multiple other factors. “Total Probability” (TPROB), used to guide final patch placement, is based on:

$$\begin{aligned}\mathrm{TPROB}_{ij} = {} & \mathrm{PROB}_{ij} \times \mathrm{ELASTICITY}_{ij} \times \text{Function (HISTORY)} \\ & \times \text{Function (PROTECTED)}\end{aligned}$$

where TPROB_{ij} is the total probability for LULC type i in ecoregion j; PROB_{ij} the baseline probabilities for LULC type i in ecoregion j, from regression results; $\mathrm{ELASTICITY}_{ij}$ the Scenario-prescribed elasticity for LULC type i in ecoregion j; HISTORY the age since last change in condition or type for each pixel; PROTECTED the pre-defined protected areas, excluding or limiting change.

Ecoregion specific elasticity values, defined from 0 to 1 for each possible transition type, are multiplied by baseline probability values, with low values diminishing (or effectively eliminating, with “0” values) the possibility of a specific transition occurring at that location, and “1” values maintaining baseline probability. The History variable can likewise be used to affect baseline probabilities. In this application, History was primarily used to assist in a better representation of typical forest-cutting cycles in the Southeast. As mentioned previously, Gresham (2002) states likely harvest cycles of 20–25 years for *Pinus taeda* (i.e., loblolly pine) and other southern pine species in this area. Decision rules were incorporated to

incrementally adjust forest cutting probabilities (i.e., the “disturbed” class) for forest areas with stand ages (HISTORY) less than 20, with full probabilities retained for age classes above 20. A protected areas database, consisting primarily of areas of low probability for change such as wildlife refuges and similar regions, was used to define decision rules greatly lowering probabilities of change within these regions.

TPROB values are calculated for each individual land-cover type and for each unique ecoregion. Patch placement is determined by TPROB image characteristics and the scenario-defined “clumpiness” parameter described previously, with patch placement limited to relatively high probability zones. Patch placement proceeds iteratively, land-cover type-by-land-cover type, ecoregion-by-ecoregion, until the annual prescription is met. Due to the iterative process, with individual land-cover types placed on the landscape independent of other land-cover type change, multiple “new” landscape patches may possibly cover the same area. In case of competition for a given landscape patch, the patch is assigned to the land cover with the highest TPROB value, potentially resulting in the need for additional patches for the unselected land-cover type.

Once the yearly prescription has been allotted, modeling proceeds to the next yearly iteration. TPROB values are recalculated based on the new beginning year’s land-cover distribution and changes in HISTORY values, and the spatial allocation process is repeated. Note that while it is very easy to incorporate changing land-cover prescriptions from year to year, such as changing demand for individual land covers in response to potentially modeled variations in important drivers, no such attempt was made to do so with this simple application in the Southeast. Annual demand for individual land-cover types was assumed to remain constant, so the same annual prescription was applied for each subsequent year after 1992, through 2050. Individual land-cover data products, as well as HISTORY images, were archived for each date, resulting in a 59-layer data stack for each, allowing for complete historical reconstruction of model results from 1992 to 2050.

4. Results and discussion

The current FORE-SCE model application is focused on the spatial allocation of a specific land-cover prescription. “Demand” for future land-cover proportions was predetermined by extrapolating Land Cover Trends results. Model construction ensured the total amount of change per ecoregion matched demand, as individual patches of change were continually placed on the landscape for every annual iteration until “demand” was met. We can thus successfully meet any ecoregion prescription for total change for individual land-cover types.

Model validation and assessment of total change on an ecoregion-by-ecoregion basis is thus unnecessary for this application. In terms of assessing the success of the spatial allocation approach, the primary question is the distribution of change patches within ecoregions. In a qualitative analysis, resulting land-cover patterns look “reasonable” in that urbanization is primarily occurring at the urban fringe, clear-cutting is occurring in areas where conifer plantations have dominated, and other land-cover changes look to be occurring in logical locations (Fig. 4).

Absolute validation of land-cover projection models is extremely difficult, and it is often impossible to validate future land-use patterns beyond the use of qualitative analysis and expert knowledge (Verburg et al., 1999). Acquisition of suitable reference data for projected data sets is an obvious issue. However, because we began our model runs in 1992, we could potentially use land-cover data sets created post-1992 for model assessment. The problem lies in acquiring consistent, multi-date land-cover products. Our beginning landscape was a modified version of the 1992 NLCD. The USGS has since produced a 2001 NLCD product (Homer et al., 2007), but have altered production procedures and thematic classes mapped, making a direct comparison between the two pointless. Because the 2001 NLCD product no longer used the 1992 NLCD class “mechanical disturbed”, associated with forest cutting, it would be impossible to even begin assessing the dominant form of land-cover conversion in our study area using NLCD data.

The USGS Land Cover Trends data used as a basis for constructing “Demand” for this application offered hope for analyzing model performance. However, Land Cover Trends used a sampling approach consisting of randomly distributed 10-km blocks, while this FORE-SCE application produced wall-to-wall land-cover maps. While the manual interpretation approach used by USGS Land Cover Trends provided a superior source of potential ground truth data for the 1992–2000 time period, the question arises: How does one assess model performance of a wall-to-wall land-cover map with Land Cover Trends sample blocks?

Given the random distribution of Land Cover Trends sample blocks within an ecoregion, we would expect some blocks to fall in high-change areas and some in low-change areas, depending upon underlying local drivers of change. FORE-SCE modeled distributions of 1992–2000 change should show similarity to Trends sample block distributions of change. Given the focus on forestry activities in this study, we examined within-ecoregion distributions of 1992–2000 clear-cutting as modeled by FORE-SCE by comparing to empirically mapped change within Land Cover Trends sample blocks.

Fig. 5 shows the amount of clear-cutting mapped by Land Cover Trends and modeled by FORE-SCE from 1992 to 2000 for each of 25, 10-km sample blocks within the Southwestern Appalachians ecoregion, one of the few ecoregions completely contained within the study area. With FORE-SCE prescriptions resulting in projected clear-cutting levels matching Land Cover Trends estimates for the entire ecoregion, one would expect within-sample block measurement of clear-cutting to be similar if projected change was distributed properly. FORE-SCE mapped a slightly higher level of clear-cutting within the blocks (8362 ha) than Land Cover Trends measured (7129 ha), meaning the amount of clear-cutting mapped by FORE-SCE was proportionally slightly higher within sample blocks and slightly lower in the ecoregion area outside of sample blocks. Per-sample block levels of clear-cutting were compared as well between mapped and modeled land cover, with a correlation of 0.71. Graphically, Fig. 5 shows a similar pattern between the two, with much higher rates of clear-cutting in sample blocks

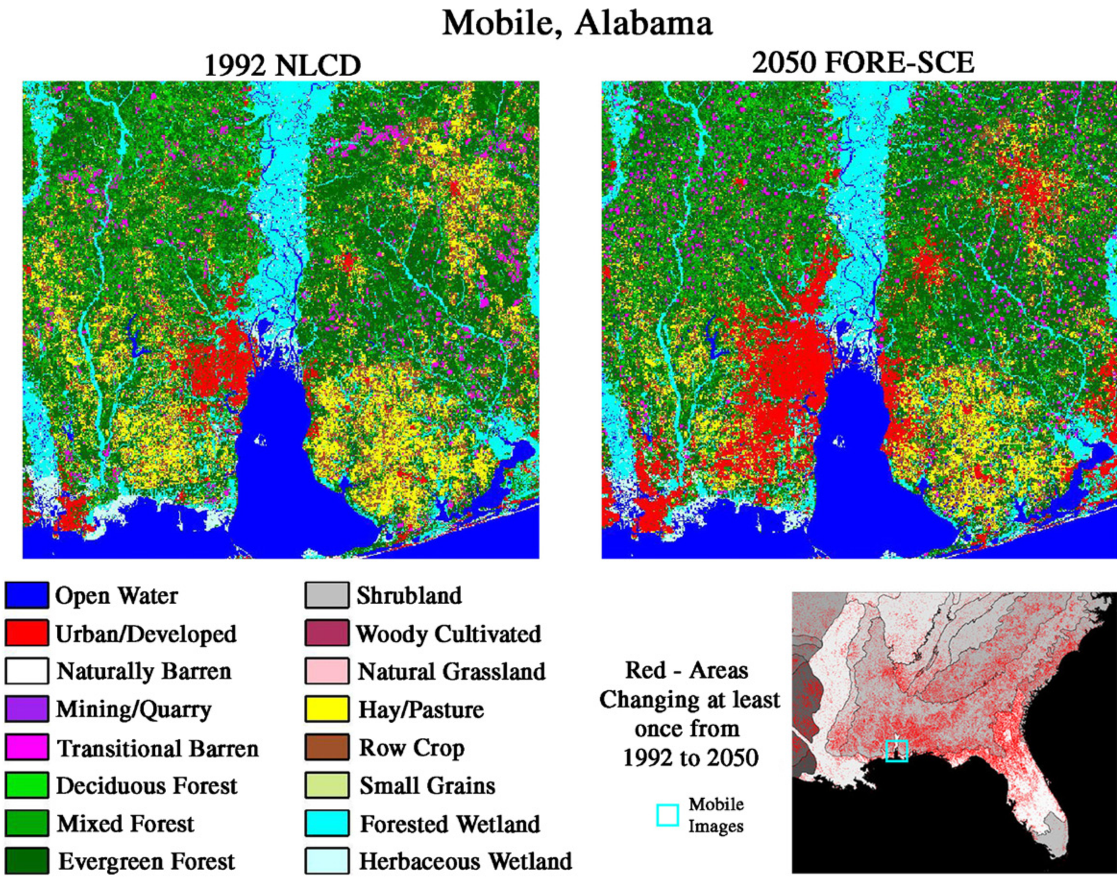

Fig. 4 – Modeled 1992–2050 land cover, Mobile, AL: starting 1992 land cover and modeled 2050 land cover for a portion of the study area around Mobile, AL. Extrapolations of ecoregion-specific Land Cover Trends mapped 1992–2000 land cover result in a landscape with continued significant forest cutting activity (transitional barren class), loss of agricultural lands (especially hay/pasture) to more profitable pine plantations, and considerable urban growth.

in the southern part of the ecoregion, although there are some local differences.

Fig. 6 similarly shows clear-cutting mapped by Land Cover Trends and modeled by FORE-SCE for the Southern Coastal Plain ecoregion, another ecoregion completely contained within the study area. Overall within-sample block levels of clear-cutting were again similar, with Land Cover Trends mapping 13,728 ha and FORE-SCE modeling 12,156 ha. Per sample block levels of clear-cutting show a correlation of 0.67 between mapped and modeled land cover. Once again, there are some local differences, but the overall distribution is similar, with both showing much higher levels of clear-cutting in the north-central and northeastern part of the ecoregion and very low levels in the southern part.

While general agreement in spatial distribution between intensively mapped and measured Land Cover Trends results and FORE-SCE modeling results is certainly encouraging, it is a mistake to assume that strict pixel-by-pixel comparisons between reference and modeled land cover should match perfectly (Sohl et al., 2007). There are inherent stochastic elements of natural and human systems which drive land cover and land-cover change, with model differences at least partially due to the stochasticity of the two systems being compared (White and Engelen, 2000). It remains to be determined whether the block-by-block correlations of 0.67 and 0.71 provided in Figs. 5 and 6 are "good" results for a land-cover change model. Significant work remains in improving our ability to adequately characterize what constitutes a successful modeling effort.

We do recognize several factors which potentially affected our representation of the spatial distribution of change. Our baseline 1992 land-cover product (NLCD) lacks the absolute local accuracy of Land Cover Trends-mapped land cover, and as it was used for reference land cover for logistic regression analyses, NLCD misclassification can affect the local accuracy of the regression-based probability surfaces. Given that a modified version of NLCD served as our beginning 1992 land cover, misclassification also directly influences land cover available for change, given the prescribed "elasticities" defining transition probabilities for each unique land-cover transition.

It is also extremely likely that within-ecoregion distribution of change would be even better represented if probability-of-occurrence surfaces were constructed ecoregion-by-ecoregion, rather than for the entire study area as a whole. We recognized that we were sacrificing within-ecoregion accuracy of the probability surfaces by using this approach but simply did not have the resources to model probabilities ecoregion-by-ecoregion. Additionally,

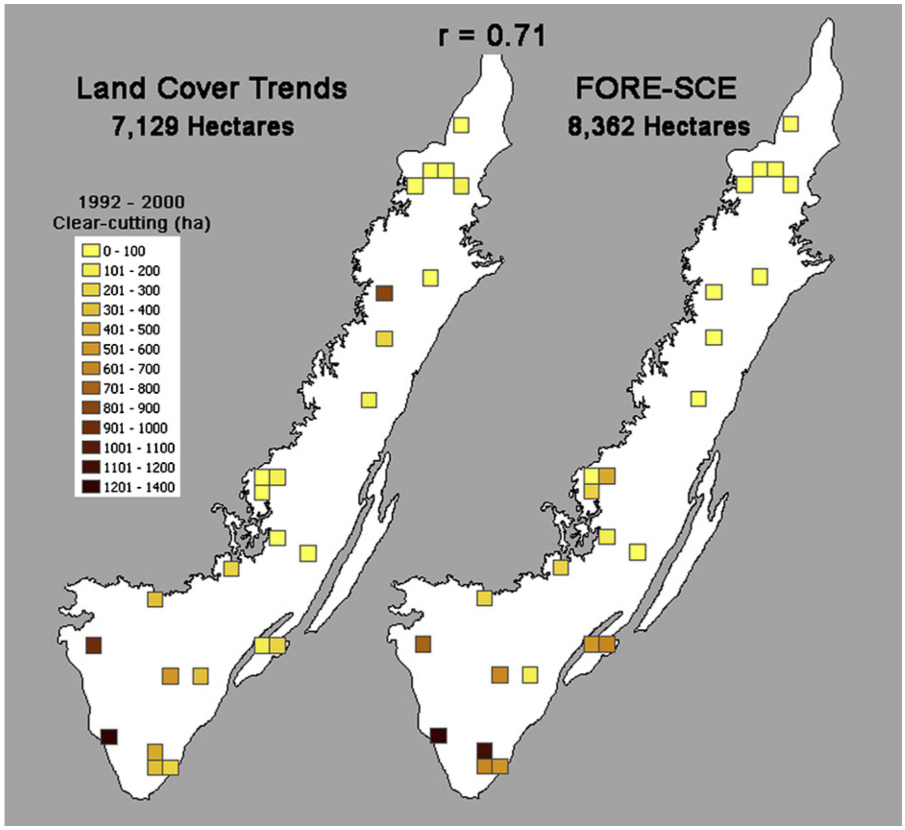

Fig. 5 – Southwestern Appalachians forest cutting: total amount of 1992–2000 clear-cutting in 25 sample blocks in the Southwestern Appalachians ecoregion, as measured by the Land Cover Trends project (left), and as modeled by FORE-SCE (right). FORE-SCE modeled slightly higher levels than expected within Land Cover Trends sample blocks. The overall spatial pattern of clear-cutting was similar ($r = 0.71$), with higher levels of clear-cutting in the southern part of the ecoregion.

improvements in the representation of spatial distribution could be made by the use of mixed regressive-spatial autoregressive models. We spatially stratified our initial random sample of 50,000 points in a simple attempt to lessen the effects of spatial autocorrelation, but we used a simple linear regression model. Overmars et al. (2003) suggest using Moran's *I* to initially identify and quantify spatial autocorrelation in a land-use analysis and using a mixed regressive/autoregressive model rather than a simple linear model when spatial autocorrelation exists. They showed such an approach can account for spatial autocorrelation and result in a much better goodness-of-fit for the model. We are examining each of these issues for future FORE-SCE applications.

While overall regional rates of change are correctly represented, and comparisons to Land Cover Trends results show similar spatial distributions within ecoregions, we are continuing to pursue other measures of model calibration and validation. A significant portion of our current and future research is devoted to development of cross-walk techniques for utilizing Land Cover Trends-based landscape pattern metrics information for the parameterization and validation of ecoregion change. For example, our "clumpiness" parameter, driving the clumped or dispersed nature of change patches within an ecoregion, is currently estimated for each land-cover type within an ecoregion with an iterative approach involving the qualitative examination of Land Cover Trends results and subsequent distributions of change. We are investigating less manually intensive processes for parameterizing and modeling the dispersion/clumpiness of patches by quantifying these measures from Land Cover Trends results and using them for FORE-SCE model parameterization.

We are also investigating better representation of patch size and configuration. Currently, patch size is simply modeled by using Land Cover Trends-measured mean patch size and standard deviation, and assuming a Gaussian distribution. We realize this is an obvious simplification and that patch size distributions are likely not all Gaussian. We are attempting to refine our representation of patch shape by individually modeling patch size distribution for each land-cover type for each ecoregion.

The switch to the use of the "patch library" approach for determining patch shape/configuration was partially made to accommodate the need for much faster model run times than the previous patch-growing procedure. Annual model iterations in the southeastern United States would not have been possible without the change, and faster model processing times also immeasurably improve our ability to "tweak" model parameters and performance, given our ability to quickly generate modeled output for multiple model runs. However, we believe the switch to a patch library approach will prove to be advantageous for other reasons as we move forward. Land

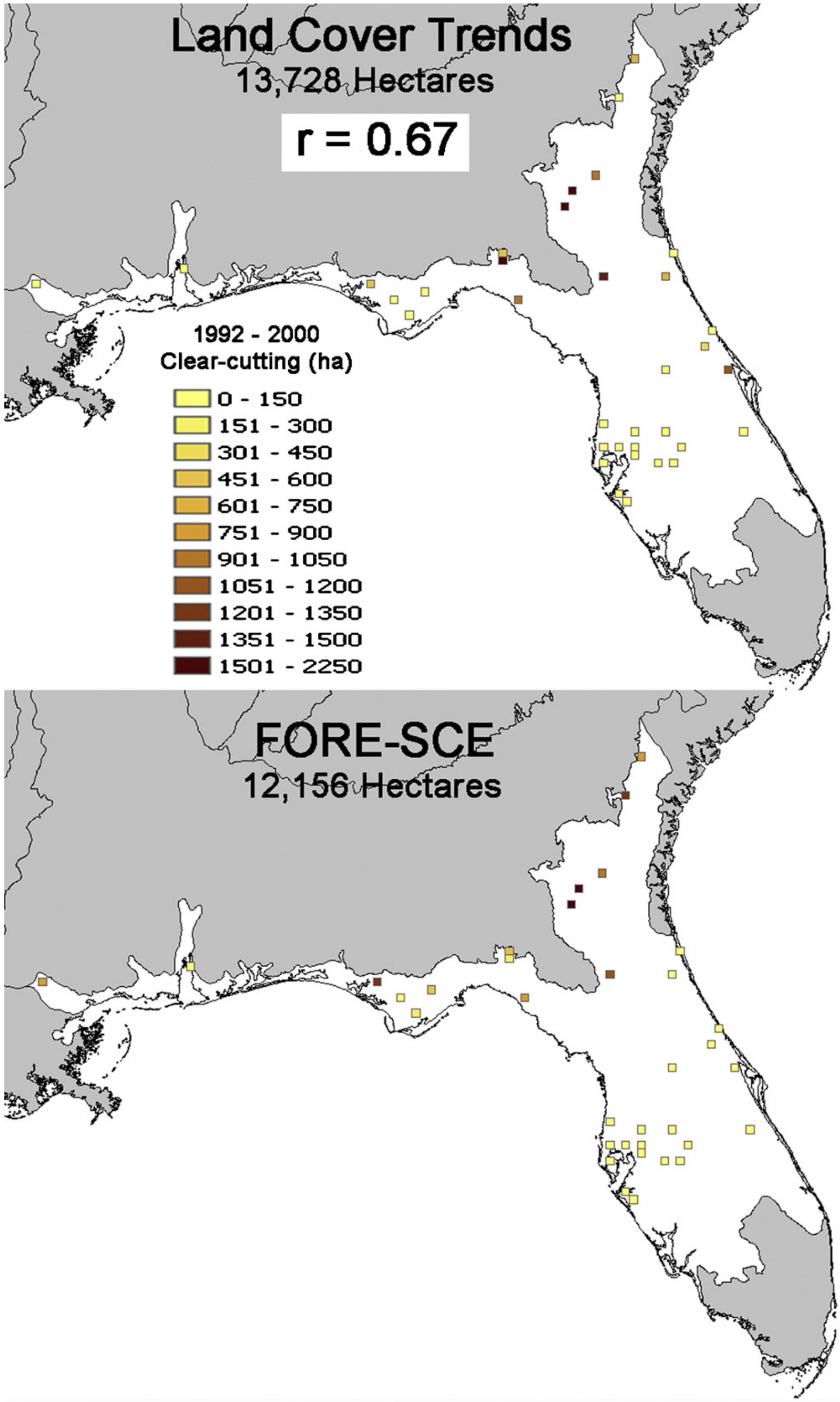

Fig. 6 – Southern coastal plain forest cutting: total amount of 1992–2000 clear-cutting in 35 sample blocks in the Southern Coastal Plain ecoregion, as measured by the Land Cover Trends project (top), and as modeled by FORE-SCE (bottom). FORE-SCE modeled slightly lower levels than expected within Land Cover Trends sample blocks. The overall spatial pattern of clear-cutting was similar ($r = 0.67$), with higher levels of clear-cutting in the northern part of the ecoregion and very little in the southern half.

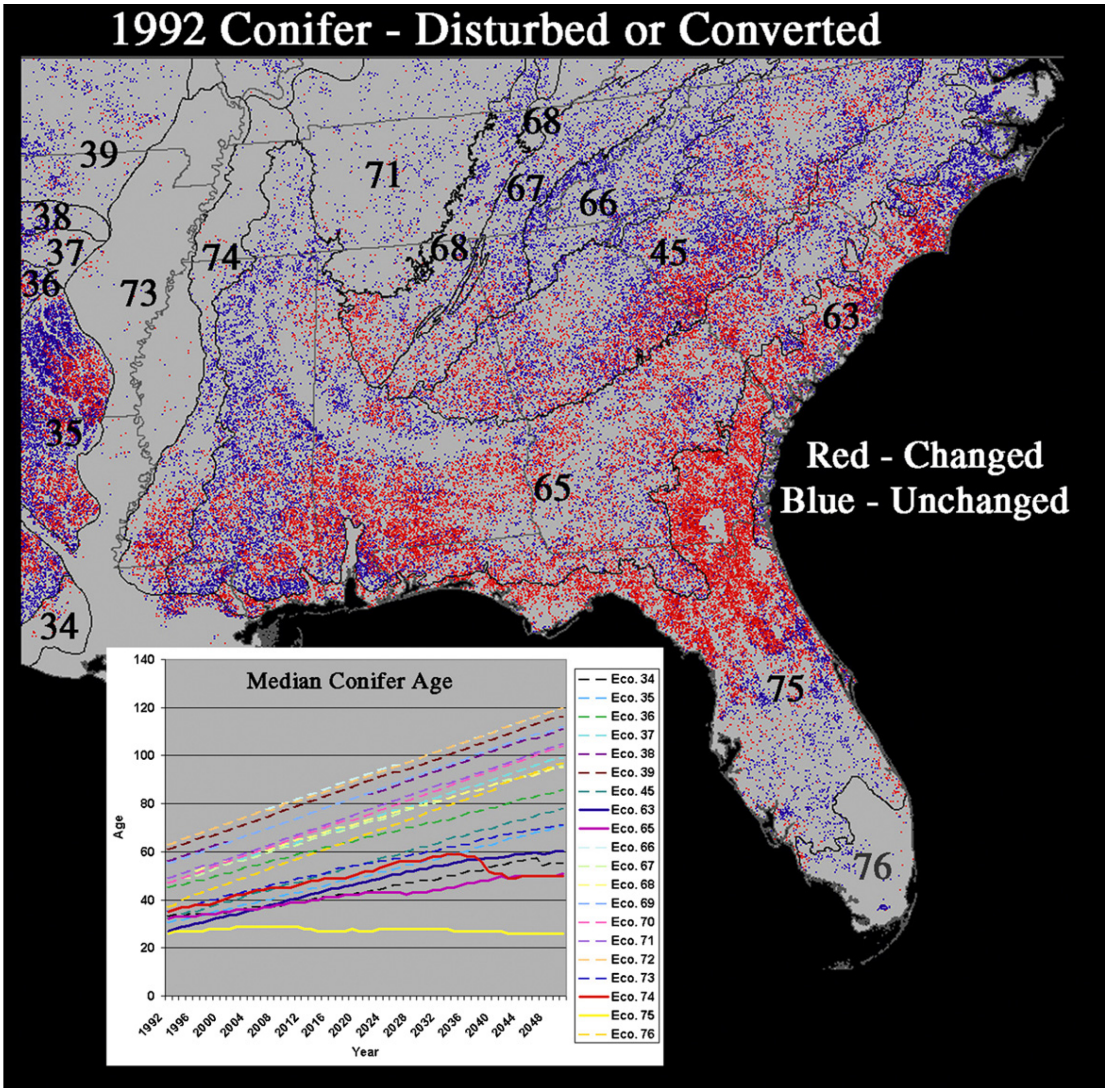

Fig. 7 – Modeled forest cutting: areas of 1992 conifer that were projected to be disturbed (clear-cut) or converted to another land-cover class by 2050. Extremely high levels of cutting in the Southern Coastal Plain ecoregion (75) results in a median conifer age which declines slightly from 1992 to 2050, while conifer age in the heavily forested Southeastern Plains (65) struggles to rise. The Mississippi Valley Loess Plain (74), characterized by significant conversion of agricultural land to pine plantations in the 1992–2000 Land Cover Trends data, shows an initial slow increase in median conifer age, followed by a sharp decline as the lands converted to pine plantation begin to reach stand ages suitable for cutting.

Cover Trends data can help us characterize patch shape as well as size, resulting in patch libraries, which represent the unique patch characteristics found across different land-cover types and ecoregions. Continued development of robust patch libraries for each location and land-cover type will allow us to more realistically portray the characteristics of new patches of land cover than did the older patch-growing procedure. In addition, the switch to the patch library approach and subsequent improvements in model processing time allows us to potentially use a Monte Carlo approach for projecting change probabilities, rather than static hard-coded land-cover projections.

The addition of the history variable, along with the establishment of initial forest stand age and guided by some simple decision rules, allowed us to track forest stand age over time (Fig. 7). The advantage of our approach is simplicity, a necessity when modeling the entire suite of landscape changes, not just forestry changes. We lack the complexity that some forestry-specific models have in addressing forest structure issues (PnET-II, LANDIS, SRTS), and we are not able to directly provide biomass, net primary production, and other biophysical measures required by our climate partners. However, our approach does provide existing age class on an annual basis. Estimates of stand volume and other biophysical parameters can thus be estimated based on age-class, and timber-volume relationships can be established for individual ecoregions.

While we feel the general approach can provide adequate information for a broad application such as the sensitivity of climate to land-cover change, several factors require attention if we are to improve our projections of forest activity and

stand age. A primary consideration is acquiring and utilizing spatially representative land ownership information, rather than using simple decision rules based on our protected areas database. Forest land in the southeastern United States is largely in private ownership (89%, Conner and Hartsell, 2002) where land-use decisions have long been a culmination of the individual decisions of hundreds of thousands of landowners (Wear et al., 2004). A better representation of land ownership, along with a focused model of how land-use decisions are made, would obviously improve model results. Similarly, we recognize a better representation of forest management is desirable. For example, Siry (2002) notes dramatic increases in forest productivity with improved tree selection, fertilization, and controlling non-desirable vegetation on managed plots.

These direct model improvements are currently beyond the scope of FORE-SCE. However, we note that Wear et al. (2004) stated that for forestry models, models are primarily estimated at the county level. Rather than using historical trend extrapolation, and rather than developing our own focused forestry model, FORE-SCE *could* directly integrate PnET-II (Sun et al., 2000; Liang et al., 2002; McNulty et al., 1996) or similar county-level forestry projections and spatially allocate forest cutting and regrowth within each county at moderate to high spatial resolutions. FORE-SCE can capitalize on more thematically focused studies for other land-cover sectors as well, as we could easily incorporate county-level demographic projections to spatially map regional urban growth or use county-level agricultural models to spatially map agricultural changes.

Finally, in this approach, land-cover prescriptions were static extrapolations of existing trends. We feel more comfortable projecting at shorter time scales (10–25 years) with this approach, rather than the 58 years actually modeled. Given the use of the data by our climate partners as source data for performing a sensitivity analysis on the effects of land-cover change on climate, and as a proof-of-concept for our spatial allocation approach, extending the model projections 58 years allowed us to better understand our strengths and weaknesses, especially in regard to tracking a dynamic forestry industry.

5. Summary

This application required the development of projected land-cover products for a large geographic region, moderate spatial resolution (250 m), and broad thematic focus covering the entire suite of land-cover changes occurring in the study area. Moreover, resources and schedules demanded an approach that could be performed quickly and efficiently. This application in the southeastern United States has shown that FORE-SCE can successfully project prescribed levels of change, no matter the source for that prescription. The current FORE-SCE's structure obviously focuses on the spatial allocation of landscape change, with demand for changing proportions of individual land-cover types provided by extrapolating baseline historical trends. The incorporation of history tracking and decision rules can provide regional estimates of forest structure changes. The model modifications allow our climate partners to construct unique biophysical parameterizations based not only on land-cover type but also on forest age. This application has demonstrated our ability to use a purely geographic approach for distributing prescribed change across the landscape, a valuable approach when trying to account for a multitude of different land-cover types, operating across many different states and ecoregions, at moderate spatial resolution. Given a land-cover prescription, the current form of FORE-SCE provides a projected land-cover product capable of supporting a variety of applications wishing to examine the potential impacts of regional land-cover change.

FORE-SCE also has the potential to do much more. The current application used an extrapolation of empirically measured Land Cover Trends data, but there is no reason why other sources outlining demand for individual land-cover types cannot be used. We have laid the groundwork to provide a flexible modeling environment capable of directly integrating more thematically focused analyses. While we are in the process of developing our own "demand" module for determining projected proportions of individual land-cover types based on responses to changes in drivers of change, the basic FORE-SCE structure can also be used to capitalize on other focused land-change studies and spatially allocate change based on their coarser resolution results.

Be it the extrapolation of historical Land Cover Trends or the use of other sources for determining demand for individual land-cover types, the FORE-SCE structure is very effective at providing spatially detailed projections of land cover. Future research will concentrate on the improvements noted above in the spatial allocation of change and the development of theme-based demand modules concentrating on individual land-cover types. Finally, we are working with partners in applications ranging from climate to carbon impacts to examine feedbacks between land-cover change and the biophysical processes affected by change.

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