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APPLICATION OF LINKED REGIONAL SCALE GROWTH, BIOGEOGRAPHY, AND ECONOMIC MODELS FOR SOUTHEASTERN UNITED STATES PINE FORESTS

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SUMMARY

The southern United States produces over 50% of commercial timber harvests in the US and the demand for southern timber are likely to increase in the future. Global change is altering the physical and chemical environmental which will play a major role in determining future forest stand growth, insect and disease outbreaks, regeneration success, and distribution of species across the region. Therefore, it is necessary to better understand the relationships between soils, forest composition, growth, and economic demand to determine whether forests in the Southern US can satisfy future forest resource demands. Integrated models can be a useful tool to understand future timber supply and demand under changing environmental and social conditions. This paper linked DISTRIB, a forest biogeography model; PnET-II, a lumped parameter forest productivity model; and SRTS, a economic model of southern timber markets to attempt to understand the interactions between forest distribution, productivity and economics. As an example of model linkage, we examined the impact that the Hadley2Sul general circulation model predictions of climate change would have on southern US timber supply, harvest and geographic distribution. The results of the linked models demonstrate the inertia of the forest ecosystems and economics to changing environmental conditions. Despite a 3°C increase in mean annual air temperature, regional forest productivity, volume and harvest were not greatly altered. The models did predict shifts in the pine range, and inter-regional changes in forest harvest. Results of the linked models are presented and the need for expanded research on linked dynamic model development to predict future US timber supply and demand are discussed.

INTRODUCTION

Within the southern US, 18% of the forested area (18.8 million ha) is comprised of highly productive southern pine plantations. (Mickler, 1996). *Pinus taeda* L. (loblolly pine), *Pinus elliottii* Engelm. (slash pine), *Pinus palustris* Mill. (longleaf pine) represent 80% of the pine plantation growing stock. These forests provide over 50% of the US timber supply (Powell et al., 1993). Timber is either the first or second highest valued harvestable commonity across the southern US, accounting for almost 40% of the combined total of agricultural and timber revenue (Hayes, 1990). Long-term forest sustainability is vital to the continued economic prosperity within the region.

During the last ten years, the earth has experienced an increase in the occurrence of temperature and precipitation extremes (National Science and Technology Council, 1999), which could be symptomatic of a change in global climate. Although there is debate regarding the amount of climate change that can be attributed to natural variability and cycles, (Intergovernmental Panel on Climate Change, 1996), there is a general consensus that human atmospheric inputs of carbon dioxide and other gases are increasing global surface air temperatures. These increases in air temperature are projected to continue well into the next century. Recent general circulation model (GCM) runs predict varying rates of global warming during the next century. For example, the Hadley Centre's

Second Generation Coupled Ocean-Atmosphere GCM, Hadley Centre Couple Model version 2 (HadCM2Sul), predicts an approximate increase of 3.0° C in mean annual air temperature by 2100 (Climate Impacts LINK Project, 1999). This degree of climate change would have significant impacts on United States forest productivity (Gates, 1993). Reductions in forest productivity could have a substantial impact on southern timber production and serious economic implications to the southern US (de Steiguer and McNulty, 1998), while increases in forest productivity could help stimulate growth of the region's forest sector (Alig et al., 1998; Burton et al., 1998). However, the interactions between soil, climate, forest growth and distribution, and forest economics are complex. Models can provide a tool to test our understanding of these complex relationships and project future conditions based on current information.

The objective of this paper is to present an integrated modeling framework for predicting how climate change could shift the biological range of southern pines, how growth could change within the range, and how climate change could impact timber market outcomes within the current range. We will discuss model linkages, uses, limitations, and future model development to better allow forest managers and policy makers with improved understanding of climate change impacts on southern forests.

METHODS

This paper linked DISTRIB, a forest biogeography model; PnET-II, a lumped parameter forest productivity model; and SRTS, a economic model of southern timber markets to attempt to understand the interactions between forest distribution, productivity

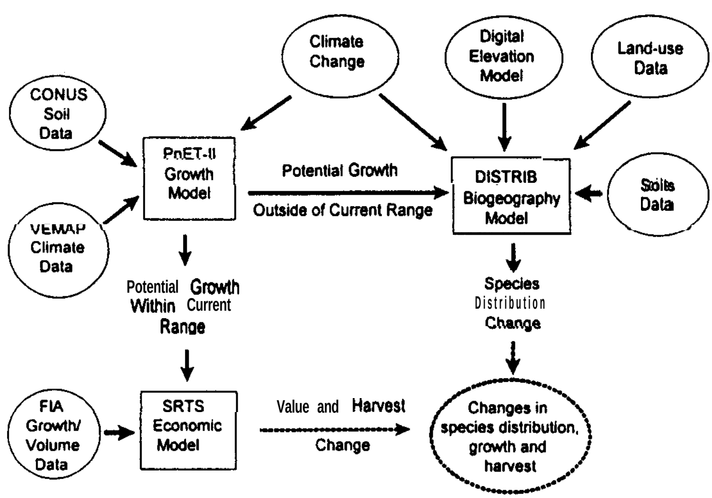


Figure 1 Linked forest process, biogeography, economic model structure.

and economics. Each model will discussed separately and interactively (Figure 1).

- **Forest Process Model**

PnET-II is a forest process model developed to predict forest productivity and hydrology across a range of climates and site conditions (Aber and Federer, 1992; Ollinger et al., 1995; McNulty et al., 1998). Model descriptions (Aber and Federer, 1992; Ollinger et al. 1995) and validation (Aber et al., 1995, McNulty et al., 1996) have been previously published. This paper provides a general overview of model structure, data inputs, and model outputs.

Table 1 **PnET-II** model values. (*) values were derived specifically for loblolly pine. All other parameters were general vegetative values for pine species.

Parameters **Description**	Parameter Abbreviation	**Value for Loblolly Pine Stand**
Intercept of the regression relationship between max. photosynthesis and N concentration (μ mol CO_2/g leaf/sec.)	AmaxA	1.92
Slope of the regression relationship between max. photosynthesis and N concentration (μ mol CO_2/g leaf/sec.)	AmaxB	39.64
Optimum air temperature (°C)	PsnTOpt	28
% foliage N concentration (g N/g leaf)	FolNCon	0.9
Specific leaf weight (g/projected m2 leaf)	SLW	200
Half saturation light level (μ mol/m2/s)	HalfSat	291
Light Extinction Coefficient	K	0.5
Growing Degree Days for leaf to start growing(°C)	GDD FolStart	900
Foliage retention time (year)	FolReten	2.0
Water Use Efficiency constant (mg C/g H_2O)	WUE	11.2
Soil Water Holding Capacity (cm) in the rooting zone (2 m)	WHC	20
Canopy Interception/Evaporation Fraction	PrecIntFrac	0.15

PnET-II calculates the maximum amount of leaf-area that can be supported on a site based on the soil, climate, and tree species specific vegetation attributes (Aber et al., 1995). The model assumes that leaf area is equal to the maximum amount of foliage that could be supported due to soil water holding capacity, species, and climate limitations (Table 1). The model does not account for differences in sites due to insect, disease, or specific management activities (i.e., burning or thinning).

Predicted net primary productivity (NPP) is a principle model output and is calculated as total gross photosynthesis minus growth and maintenance respiration for leaf, wood, and root compartments. Gross photosynthesis is first calculated without water stress effects as a function of temperature, foliar nitrogen (N) concentration, and vapor pressure deficit. Potential transpiration is calculated from potential gross photosynthesis and water-use-efficiency. Actual transpiration is a function of potential transpiration and available soil water. The latter quantity is related to the soil water holding capacity, a soil moisture release parameter, and incident soil water. After the water balance is updated, actual gross photosynthesis is calculated from water stress and potential gross photosynthesis. Wood, root, and leaf respiration is a function of the current and previous month's average minimum and maximum air temperature.

■ Forest Biogeographic Model

The forest biogeographic model DISTRIB was used to examine the impacts of climate change on southern forest distribution. We used regression tree analysis (RTA), also known as classification and regression trees, to decipher the relationships between environmental factors and species distribution (Iverson and Prasad, 1998; Iverson et al., 1999). RTA is a recursive data partitioning algorithm that initially splits the data set into two subsets based on a single best predictor variable (the variable that minimizes the variance in the response). It then does the same on each of the subsets and so on recursively. The output is a tree with branches and terminal nodes. The predicted value at each terminal node is the average at that node, which is relatively homogeneous (Clark and Pergibon, 1992). Regression trees were generated in S-PLUS (Statistical Sciences, 1993), using the RPART module developed by researchers at Mayo Clinic (Themeau and Atkinson, 1997). Species importance value (based on basal area and number of stems) was the response variable (ranging from 0-200), with the 33 predictor variables (Table 2).

The response predicted by RTA for zero values of the species importance value (IV) was almost always a fraction less than one. Through testing across all species, we determined that predicted IV scores less than the threshold of 1.00 for loblolly pine and 2.04 for slash pine were essentially zero and were set as such. The predictions of IV classes were then output to Arc/Info for mapping, using Unix tools and Arc/Info's Arc Macro Language (Environmental Systems Research Institute, 1993).

Once the regression trees were generated, they were used to generate not only predictive maps of current distributions, but also potential future distributions under the scenarios of a changed climate. We did this by replacing the climate-related variables in our predictor variable set with those based on the climate scenarios. The previously established regression trees then were used with the new predictive variables, and the data output to Arc/Info as before. Importantly, each time we change precipitation, temperature, and PET were held constant, while precipitation and PET were held constant when temperature was changed. PET was never changed from the current situation. Of course, these types of single dimension changes are not anticipated, but this exercise reveals the relative importance of temperature vs. precipitation in global change outcomes.

There are advantages to using RTA for the DISTRIB model, which covers such a wide spatial domain, over classical statistical methods (Breiman et al., 1984; Michaelson et al., 1994; Iverson and Presad, 1998). First, RTA is adept at capturing non-additive behavior, where relationships between the response variable and some predictor variables are conditional on the values of other predictors. For example, in our study, the factors associated with the northern range limits for pines may be quite different from the factors regulating the southern limit of the species. This advantage allows, a stratification of the country so that some variables may be most related to the IV of species A for a particular region of the country, but a different set of variables may drive its importance elsewhere. Second, numerical and categorical variables can easily be used together and interpreted, because RTA converts continuous data into two categories at each node. The outcome is a set of step functions that provides a better capturing of non-

Table 2 County environmental and land-use variables used for this atlas, and reported for each county.

Abbreviation	Variable
	Climatic Factors
AVGT	Mean annual temperature (deg. C)
JANT	Mean January temperature (deg. C)
JULT	Mean July temperature (deg. C)
PPT	Annual precipitation (mm)
PET	Potential evapotranspiration (mm/month)
MAYSEPT	Mean May-September temperature (deg. C)
JARPPET	July-August ratio of precipitation to PET
	Soil Factors
TAWC	Total available water capacity (cm, to 152 cm)
CEC	Cation exchange capacity
PH	Soil pH
PERM	Soil permeability rate (cm/hour)
CLAY	Percent clay (< 0.002 mm size)
BD	Soil bulk density (g/m^2)
KFFACT	Soil erodibility factor, rock fragments free
OM	Organic matter content (% by weight)
ROCRFRAG	Percent weight of rock fragments 8-25 cm
NO10	Percent passing sieve No. 10 (coarse)
NO200	Percent passing sieve No. 200 (fine)
ROCKDEP	Depth to bedrock (cm)
SLOPE	Soil slope (percent)
ORD	Potential soil productivity, m' of timber/a)
ALFISOL	Alfisol (%)
INCEPTSL	Inceptiiol (%)
MOLLJSOL	Mollisol (%)
SPODOSOL	Spodosol (%)
	Land use/cover factors
FORST.LND	Forest land (%)
CROPS	Cropland (%)
GRAZE.PST	Grazing pasture land.(%)
DIST.LND	Disturbed land (%)
	Elevation
MAX.ELV	Maximum elevation (m)
MIN.ELV	Minimum elevation (m)
ELV.CV	Elevation coefficient of variation
	Landscape Pattern
ED	Edge density (m/ha)

linear relationships, while also providing a reasonable solution for linear relationships. Last, the variables that operate at large scales are used for splitting criteria early in the model, while variables that influence the response variable locally are used in decision rules near the terminal nodes (Moore et al., 1991). Thus we could expect that broad climatic patterns are captured higher up on the tree while more local effects (soil, elevation, etc.) determine more local distribution variations. It should be noted that since our data set is aggregated to a county level scale, RTA couldn't capture the environmental drivers that operate on species at a very fine scale (e.g., individual slopes or valley bottoms).

■ Forest Economic Model

Timber market and inventory modules are the two major components of a forest sector economic model. Market parameters are first used to solve for equilibrium price changes, where the market is defined by all of the included sub-regions. Second, the price and supply shift information from the individual regions are used to calculate harvest change by sub-region. For the analysis presented here, USDA Forest Service FIA survey units and forest industry and other private ownerships in the South were used to define 102 (51 units x 2 owner types) supply sub-regions in the model. Public lands and harvest were excluded from the model because market forces do not drive their harvest and management decisions and because they are a small component of the region's timber supply.

■ Market Model Structure

Usually market equilibrium is modeled to determine price and quantity that result from exogenous shifts in supply and demand. The Sub-Regional Timber Supply (SRTS) model was developed to link to inventory models that use timber harvest as the control variable. Thus the SRTS default mode is to take aggregate regional harvest levels and solve for the implicit demand, price, and sub-regional harvest shifts.

At the aggregate region level, SRTS models year t harvest quantities as determined by the supply function:

$$Q^S_t = Q^S(P_t, I_t, v_t)$$

And the demand function:

$$Q^D_t = Q^D(P_t, Z_t).$$

where in the reduced form, current harvests, Q_t, are a function of timber prices, P_t, and beginning of period inventory, I,, and other supply and demand shifters (v,, Z,). We assume that marginal cost is increasing in output; therefore, the harvest supply function is upward-sloping [$\partial Q/\partial P_t > 0$]. Output increases with the level of merchantable inventory available for harvesting [$\partial Q/\partial I_t > 0$]. A constant elasticity or log-linear functional form is assumed. Both of these partial effects are consistent with empirical analysis of timber supply. While these studies estimate elasticities at a broad regional level, there is little information on price or inventory elasticities at the sub-regional level. Other factors affecting supply levels (v,) might include input prices, technological factors such as land quality or management, and landowner characteristics, Some of these issues can be addressed by changing ownership or management type parameters in the model as described below.

In harvest exogenous mode, SRTS determines the price and demand consequences in each year of a given harvest level and the supply shift due to modeled inventory changes. The solution sequence proceeds as follows. The region is assumed to start in equilibrium. Since the equilibrium quantity, Q_t, and starting inventory, I,, are known, the reduced form equation can be used to solve for P_t and the implicit demand shift, Z,. An initial estimate of harvest by sub-region is found by using the same supply specification with the estimated regional price change and sub-regional inventory change to estimate harvest change by sub-region. Because the Cobb-Douglas functional form is not additive, each sub-region's harvest is adjusted proportionately to match regional harvest. The model can be run with the assumption that the sub-regional supply specifications hold and the aggregate price is found by using a binary search algorithm that determines the market clearing price by summing the supply response across sub-regions and owners. In either top-down or bottom-up mode, demand shifts or equilibrium price trends can be exogenous, and the model will solve for the remaining equilibrium parameters as described in the intensive management scenario below. The runs described below maintained the aggregate market relationship or top-down assumption.

These assumptions imply a competitive market with regions and ownerships facing the same price trend. SRTS is not a traditional spatial equilibrium model where a single point with associated transportation costs represents demand. Instead, demand is assumed to be mobile either through shifts in procurement regions (e.g., chip mills) or new capacity (e.g., OSB mills) and is assumed to respond to regional differences in stumpage prices. In this formulation, all regions and owners included in model run are assumed to follow the same stumpage price trend, although levels may differ. Harvests will be shifted among owners and sub-regions based on comparative supply advantages.

■ Inventory Model Structure

The internal inventory module in SRTS is based on USDA Forest Service Forest Inventory and Analysis timberland area, timber inventory (Figure 2), timber growth rates (Figure 3), and timber removals data. The data are classified into IO-year age class groups by broad species group (e.g., softwoods and hardwoods) and forest management type (planted pine and natural pine). FIA data by species group, forest management type, and LO-year age class are summarized for each relevant region in the analysis.

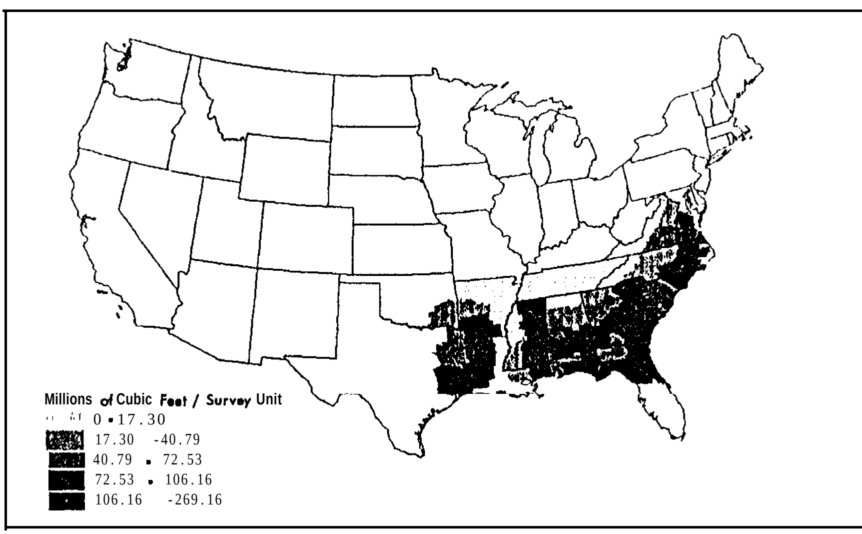
Land area trends by forest management type arc exogenous to thc model. The SRTS model uses tree and plot level data as a basis for the age and growth analyses described below.

SRTS uses lo-year agc classes and species/survey unit/owner/management type cells to account for inventory change. To avoid wide variations or "cmpty" cells, the following growth per acre (GPA) regression equation was estimated by species-group (hardwood, softwood), physiographic rcgion (dclta, coastal plain, picdmont, mountain), and managemcnt type (plantation or natural pinc):

GPA = f (state, owner, age, owner*age interaction).

A cubic age relationship was estimated. This approach allows the shape of the growth-age function to be modeled based on data from an entirc physiographic/typc combination, but allowcd the lcvel of growth to vary betwccn states, and the level and shape of the growth curvc to vary between ownčrs. In the FIA database, some plots arc not assigned ages. For thesc plots a regression relationship bctwccn plot characteristics and agc was used to assign ages to thc plots.

Harvest in SRTS is handled in thrce steps. The allocation of regional harvest to a sub-region/owner is based on supply shifts and is part of the market equilibrium calculation described below. Within a sub-region/owner, harvest is allocated across management-types and age-classes based on assigned parameters. Allocation of harvest across the five management types can be related to historical removal proportions, current inventory or growth, or any weighted combination of the abovc. For



'igurc 2 Measured FIA southern pine volume across thc 51 southern US survey units.

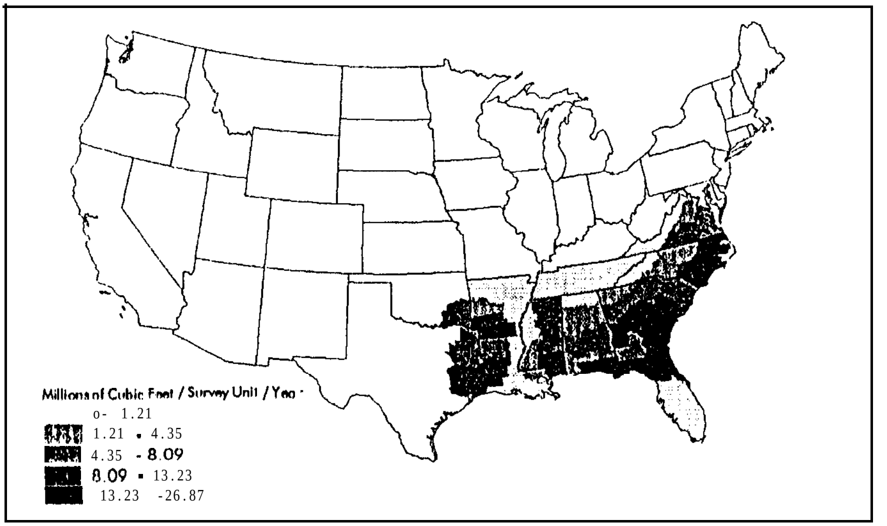


Figure 3 Measured FIA southern pine forest growth across the 51 southern US FIA survey units.

example, to allocate removals based on the average of starting removal and current, year t, inventory proportions, a 0.5 weight would be assigned to each.

Within a management type, the model can allocate harvest across age classes based on starting harvest proportions, current inventory proportions, or oldest age class first. Weighted average combinations of these procedures can also be specified. Empirical examination of harvest allocations in the FIA data indicate for all management types other than pine plantations, harvest allocations across age classes are highly correlated with inventory age class distributions.

Timberland area trends are exogenous to SRTS. The default specification is to apply one set of management type trends to each region/owner combination. For example, a one percent annual increase in pine plantation acreage would be applied to the current plantation acreage in each region. Acres added to a management type begin at age zero. Acres leaving a management type are removed proportionately across all age classes. Growing stock on these acres contributes to current harvest.

INPUT DATA

- **DISTRIB**

County level data was extracted from several sources for land east of the 100th meridian. The county was chosen as the mapping unit because it is the reporting unit for many sources of data and, for the most part except for some northern counties, has roughly the same area across the study region. We evaluated over 100 environmental/land use/socioeconomic variables for each of nearly 2,500 counties in the eastern US, and selected 33 variables for analysis (Table 2). Variables fail into one of several classes: climatic, soil, land use/cover, elevation, and landscape pattern.

- **PnET-II and SKTS**

PnET-II prediction of historic southern pine productivity was run on a 0.5” x 0.5” (approximalcly 40 x 50 km) grid across the southern US (Figure 4). This spatial resolution was aggregated to the forest survey level when input to the SRTS economic model. The southern United States is divided into 51 forest survey units by the Forest Inventory Analysis Program. The SRTS model requires volume and forest composition data at the survey level and relative forest growth from the half degree level as inputs. SRTS outputs are then aggregated to the state level for assessment.

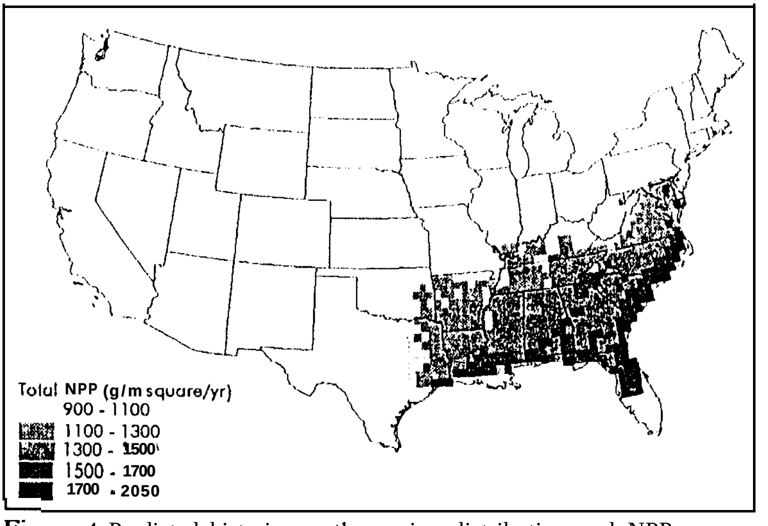


Figure 4 Predicted historic southern pine distribution and NPP on a 0.5° x 0.5” grid.

- **Climatic Factors**

DISTRIB used interpolated 10 x 10 km grid cells across the conterminous IJS of monthly mean (1948-1987) precipitation, temperature, and potential evapotranspiration that were extracted from a USEPA database (U.S. Environmental Protection Agency, 1993). From these data, we extracted January and July temperatures, calculated annual means, and derived two attributes based on their physiological importance to tree growth for this region: July-August ratio of precipitation to potential evapotranspiration (the time most prone to drought stress in the eastern

U.S.) and May-September (i.e., growing season) mean temperature. The data were then transformed to county averages via area-weighted averaging. PnET-II required monthly minimum and maximum average air temperature, total monthly precipitation, and solar radiation data on a 0.5” x 0.5” grid across the conterminous US (VEMAP, 1995).

- **Soil Factors**

The State Soil Geographic Data Base (STATSGO) was developed by the US Natural Resource Conservation Service to help achieve their mandate to collect, store, maintain, and distribute soil-survey information for US lands. STATSGO data contain physical and chemical soil properties for about 18,000 soil series recognized in the nation (Soil Conservation Service, 1991). STATSGO maps were compiled by generalizing more detailed soil-survey maps into soil associations at a scale (1:250,000) more appropriate for regional analysis. DISTRIB used 14 soil variables related to tree species’ habitat (Table 2). Weighted averages by depth and by area were calculated for county estimates of the soil variables, as detailed in Iverson et al. (1996). Additional soil information was obtained from the GEOECOLOGY databases (Olson et al., 1980), including percentage of the county in each of four soil orders (Table 2). Soil water holding capacity (SWHC) derived from the CONUS-Soil dataset (Miller and White, 1998) is the only soils parameter required by PnET-II. The SWHC data were transformed to a 0.5” x 0.5” via area-weighted averaging.

- **Land Use/CoverFactors**

GEOECOLOGY (01son et al., 1980) data were used for estimations of percent forest, crop, grazing/pasture, and disturbed land (Table 2). These estimates originated from the USDA Soil Conservation Service’s National Resources Inventory for 1977. Maximum, minimum, and variation of elevation were derived for each county from 1:250,000 U.S. Geological Survey (USGS) Digital Elevation Model (DEM) files obtained from the USGS internet site (U.S. Geological Survey, 1990). The l-km AVHRR forest cover map (Zhu and Evans, 1994) was used to generate statistics on forest-cover pattern by county. Several landscape pattern indices were calculated using FRAGSTATS (McGarigal and Marks, 1995), but only edge density was used in the final analysis. PnET-II used generalized vegetation coefficients that represented the average of southern pine species (Table 1). We derived these coefficients from field measurements and from the published literature (Aber & Federer, 1992; Aber et al., 1995; McNulty et al., 1996).

- **Climate Scenario**

Climate scenarios are useful for examining the potential impact that changing surface air temperature, precipitation or solar radiation could have on forest productivity. Recent climate scenarios project changing climate at a monthly time step to the year 2100. For the purpose of demonstrating the linked modeling framework, we have chosen to use the Hadley2Sul climate change scenario. This transient, monthly resolution, general circulation model prediction of climate change was originally developed on a 2.5” latitude x 3.75” longitude resolution (Climate Impacts LINK Project, 1999), and then subset to the 0.5° x 0.5” VEMAP grid (VEMAP Members, 1995). The scenario climate inputs were used in both the PnET-II and DISTRIB models.

MODEL INTEGRATION

▪ PnET-II-SRTS Integration

PnET-II model prediction of forest NPP were first derived from historic climate data to develop a historical grid at a 0.5” x 0.5” across the southern region (Figure 4). The model is then re-run with the Hadley2Sul GCM to examine the impact of changing air temperature, precipitation, and atmospheric CO, on potential forest productivity for each grid cell (Figure 5). The PnET-II model only predicts potential productivity because actual stand stocking is not input to the model. The relative climate change impact on forest productivity was calculated as a ratio of climate scenario productivity/ historic productivity.

Ratio values greater than 1.0 indicate that forest productivity will increase for a specific cell under climate change, while values less than 1.0 indicate that climate change will have a negative impact on forest growth. The ratio for each

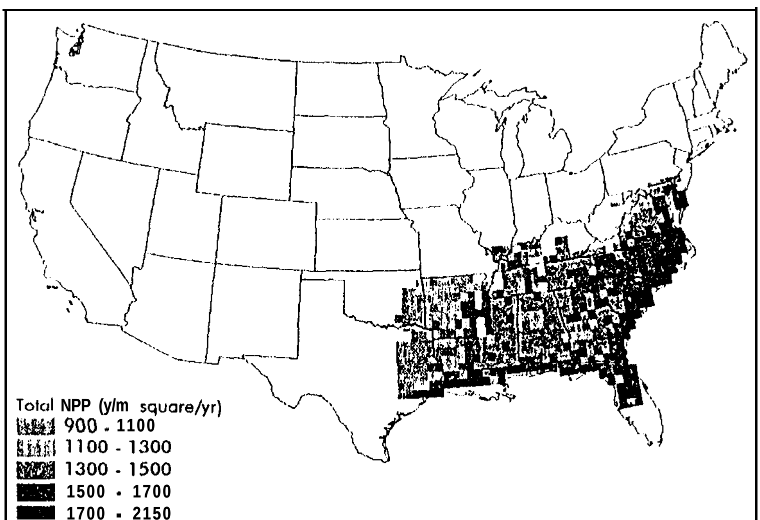


Figure 5 Predicted southern pine distribution and NPP in 2040 using the Hadley2sul climate scenario on a 0.5” x 0.5” grid.

grid cell and year was then combined with the USDA Forest Service Forest Inventory Assessment data of stand growth.

The individual FIA plot level historic forest volume and growth data is aggregated up to the survey unit scale for analysis. A GIS mask of the survey units is overlaid on the 0.5" x 0.5" PnET-II grid of productivity ratios. A weighted average of productivity is then calculated for each survey unit based on all of the predicted PnET-II grid cells. This procedure results in a productivity ratio of the climate change scenario productivity and historic climate data derived productivity at the FIA survey unit scale (Figure 6).

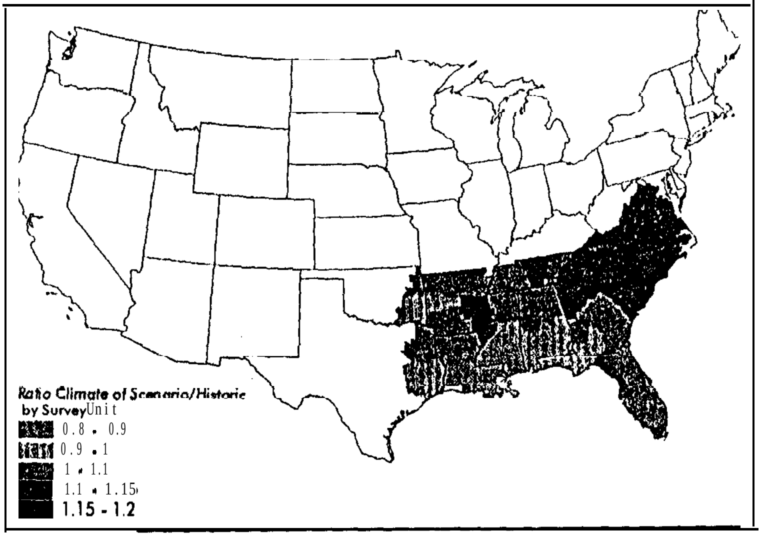


Figure 6 Predicted ratio of historic and climate scenario NPP between 2000 and 2040 regridded onto the 51 southern US FIA survey units.

To calculate climate scenario impacts on changing forest growth, the PnET-II predicted FIA survey unit climate scenario productivity ratio mask is overlaid on the FIA measured historic survey unit growth data. The climate scenario growth ratio mask is used as a multiplier to those historic measured growth rates. Model predictions of growth are expressed as cubic meters per FIA survey unit per year (Figure 3). Using this approach, specific climate scenario years or an average of several years can be examined. For this paper, we used a 10-year average productivity change around 2040 (i.e., 2035 to 2045).

- **PnET-II-DISTRIB Integration**

PnET-II predicts potential NPP as a function of climate, soils and species specific vegetation parameters for a stand. However, PnET-II does not predict the range of a forest type. Previously, FIA data has been used to delineate the range distribution of a species. All forest plots containing the three southcrn forest species wcrc ovcrlaid on thc VEMAP grid to create a mask. Thc mask was thcn placcd on top of the potential productivity map from PnET-II to produce a map of productivity within the forest range.

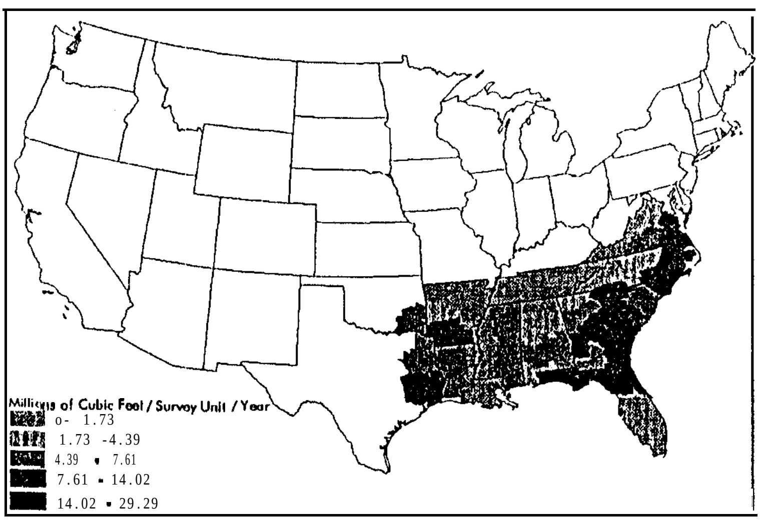
DISTRIU is an cmpirical modcl prcdicting species distribution and importance as a function of climatc, topography, and soil propertics. Thc modcl prcdictcd current ad futurc spccics distribution under historic and climatc changc sccnarios. Modcl prcdictions arc originally output at thc county lcvcl. This data was rcgriddcd to thc VEMAP grid ccll using a weighted average fore each cell. Once the data was regriddcd thc predictcd species range maps were then used as a mask of the potcntial forest productivity predictions. Finally, PnET-II predictions of current and future NPP wcrc projected within thc ranges of predicted current (Figure 4) and climatc sccnario prcdictcd (Figurc 5) spccics range from DISTRIU.

RESULTS AND DISCUSSION

■ Changcs in Southcrn Pinc Productivity

Annual changes in forest productivity wcrc the most scnsitivc of thc thrcc modcls. Although forcst productivity is partially dcpcndcnt on prcvious ycar's growth as storcd carbon for current year bud growth, most of thc currcnt ycars productivity is dcpcndcnt on individual wcathcr patterns for each year.

Using thc Hadlcy2Sul climate scenario, rcgional southern pinc growth ranged from a low of 4.7 billion ft^3 yr^{-1} to a high of 6.9 billion ft^3 yr^{-1} (Figurc **7).** This range rcprcscnts a 47% changc in intcr-annual forest growth



Figurc 7 **Predicted** annual forcst growth within each FIA survcy unit bctwccn 2035 and 2045.

varability across the southern US. At the regional scale, areas of favorable and unfavorable growth are averaged together, thus decreasing inter-annual forest productivity variation. Within a state or survey unit, the inter-annual variation would be even larger.

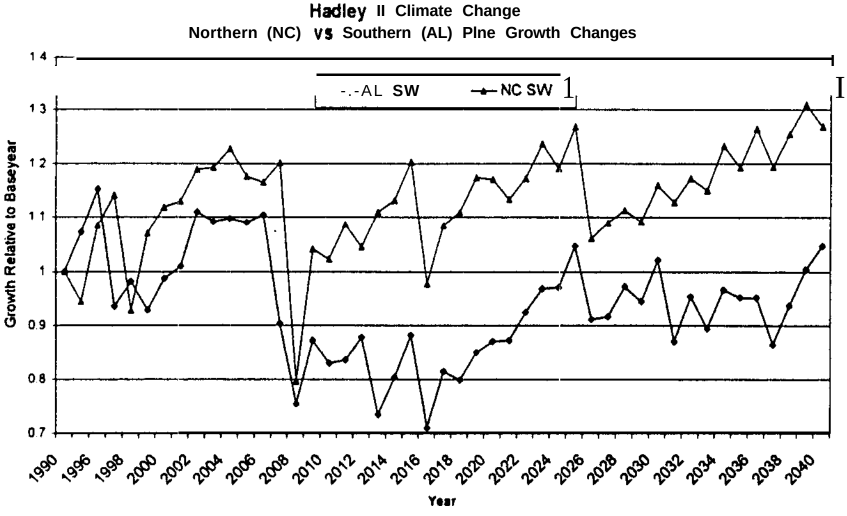


Figure 8 Ratio change between historic and Hadley2Sul climate scenario from 1990 to 2050 for FIA survey units in Alabama (AL) and North Carolina (NC).

For example, southern pine productivity in both North Carolina and Alabama responded to intra-annual changes in climate (Figure 8). The productivity ratios for North Carolina and Alabama respectively varied from 0.8 to 1.33 and 0.7 to 1.15. This represents a 66% variation from the best to worst productivity year for North Carolina and a 64% variation for Alabama. Even though the range of variability was similar, the pattern under which this variability occurred was very different.

In Alabama, the highest rates of productivity occurred in the late 1990's and were similar to productivity in North Carolina (Figure 8). Growth in each state varied randomly until 2025, after which, PnET-II predicts that a fundamental change will begin to occur between the two states. Alabama is a much warmer state than North Carolina, and more frequently has months with air temperatures that exceed the optimal range for southern pine growth. With the 3°C increase in climate mean annual climate as predicted by the Hadley2Sul scenario, productivity in Alabama begins to decrease after 2025. Historically, North Carolina has many months that are below the optimal temperature range for southern pine growth and few months that exceed the range. Therefore, the 3°C increase in mean annual air temperature brings the state closer to the optimal temperature range for pine growth and thus North Carolina becomes more productive that Alabama. The shift from the highly productive southern coastal zone (Figure 4) to the more northerly extent of the southern pine range (Figure 5) can also be attributed to increasing air temperature.

■ Changes in Southern Pine Range

Many factors other than climate determine the spatial extent of a species besides climate. DISTRIB also uses soils, elevation, and land-use which in the short-term are unresponsive to climate change. Therefore, these other limiting factors contributed to reduce the spatial shift in the southern pine range. Using current FIA data, DISTRIB predicted that southern pine forests would occupy 103.8 million ha, ranging from the southeastern coast to east Texas and central Virginia (Figure 2). The Hadley2Sul climate scenario, the coolest and wettest of most global change scenarios, caused DISTRIB to predict that the current range of southern pines would expand to 120.3 million ha, and would include all of West Virginia and parts of Ohio, Indiana, and Pennsylvania (Figure 5). This change represents a 15.9% increase in the southern pine range and moves the center of species dominance northward. DISTRIB is based on $2xCO_2$ and does not address how fast a forest type can migrate across the landscape. The historic migration rate of southern pine species is 81 m yr^{-1} (Delcourt and Delcourt, 1983). Migration is expected to be slowed by fragmented habitats as well (Schwartz, 1992; Iverson et al., 1999b), so that migration into cooler northern regions could take thousands of years. However, humans can accelerate species migration through planting. If air temperature across the southern U.S. increases by 3°C, then the commercial range of loblolly pine could be expanded northward.

■ Changes in Southern Pine Timber Markets

Since growth rates are approximately five percent of inventory, large changes in growth rates lead to much smaller fluctuations in inventory (Figure 9). In this economic scenario, real prices were assumed to remain constant. Based on the economic structure of the model, constant prices imply proportionate shifts in removals in response to inventory change. Across different regions and owners, this implies that those regions with relative growth increases will experience positive harvest responses. This tends to reduce the variation in inventory trends that would emerge from a purely biological model. Over time, the 1990 to 2040 period seems to show periods of slightly increased growth at the beginning and end of the projection period, with a decade of decreased growth from approximately 2010 to 2020. In simulations with endogenous prices, this would imply increased prices during the middle of the projection period. Due to the observed inelasticity (i.e., rigid response to prices) of both supply and demand, relatively small shifts in inventory can lead to significant price changes.

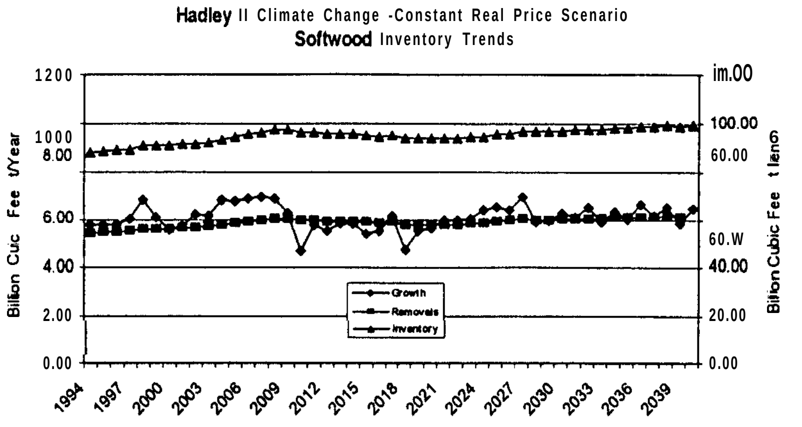


Figure 9 Regional change in southern pine removals, growth and inventory within each FIA survey unit from 1990 to 2040 as impacted by the Hadley2Sul climate change scenario.

SRTS calculated that PnET-II predicted changes in southern pine productivity would alter the location of harvested pine across the southern US. From 1990 to 2040 the majority of timber would be harvested from the most southern to the most northern current distribution of the southern pine range (Fig. 10).

- **Integrated Model Sensitivity**

The linked models demonstrated the inherent lags and buffers that regulate long-term forest productivity, economic value and distribution. Model or experimental studies cite large changes in annual productivity associated with a set range of environmental conditions over several years. As shown with this linked model, the variation in productivity can be greatly reduced when examined over longer time frames or larger geographic areas.

Although these three models represent a significant advance in linking regional forest productivity, biogeography, and economic forest models, each of the models have limitations and the integration between the models are also limited. Better understanding of these assumptions and limitations provides both direction for future research and reduces the potential for model misinterpretation.

- **PnET-II**

PnET-II predicts potential forest growth as a function of forest specific vegetation attributes, soil type and climatic conditions. There are to stand level attributed to the model so interactions between species for nutrients, water, light are not considered. Instead, the input site parameters are used to calculate the maximum rate of growth for a species. At the stand level, PnET-II predictions of growth could be an underestimate of measured growth if multiple species are using the niches below the forest canopy. Therefore, the model vegetation inputs should either represent a monocultural forest type, or as in this example, attempt to mimic the range of species positions within a canopy by using a average input value for a forest type. The light extinction coefficient, specific leaf weight, foliar nitrogen concentration, and optimal air temperature for photosynthesis will all modify canopy leaf area and forest growth.

PnET-II assumes that forest growth is limited by resource availability. External factors that can reduce forest leaf area such as herbivory, fire, or stand thinning are not considered in the model. These disturbances to the stand are incorporated into the current study with the use of growth ratios. Historic (baseline) growth rates for a FIA survey unit are compared to growth within the survey unit under a climate change scenario. The ratio-of these runs are then multiplied by historic productivity to predict future growth. This method assumes that future rates of insect damage, fire occurrence and severity, and management practices will be consistent with current instances.

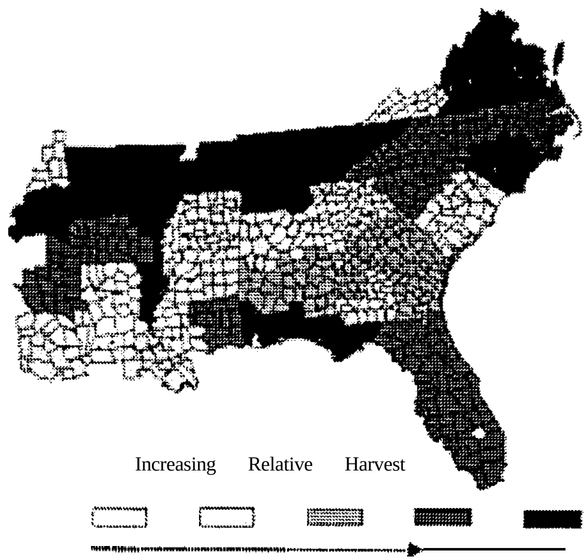


Figure 10 Predicted southern pine harvest shifts within each FIA survey unit from 1990 to 2040 across the southern US.

Forest management stocking practices may also change with CO_2 fertilization (increased forest stocking). PnET-II addresses in impact of increased atmospheric CO_2 by increasing the WUE constant within the model. However, changes in forest management are not addresesed. Additionally, in unmanaged forest stands, this method assumes that forest composition will remain constant. Shifts in predicted forest species range suggest that changes in futures forest composition are likely.

Finally, there is limited data on some model input parameters such a genetic variation and ranges in foliar nitrogen content across the southern U.S. We assume that these values are constant but proviance studies suggest that depending on the seed source, southern pine forest growth can vary by under identical site conditions. Similarly, foliar nitrogen concentration vary across the in relation to soil nitrogen availability. However, a comprehensive database on foliar variation is lacking, so an average value is used for the forest type. The combined impact of these unknown model factors could equal or exceed the changes associated climate variation.

- **DISTRIB**

The DISTRIB model assumes that the changes evaluated here are uni-dimensional, and therefore not very realistic. Second, any time multiple GIS layers from disparate sources and scales are overlaid, errors will propagate through the data (Goodchild and Gopal 1989). This impact is minimized in this study by using a large sampling unit, the county, as the common spatial unit. There is also error associated with the sampling of trees; occasionally species that do in fact reside in the county will be missed by the sampling plots. Third, the method described here does not account for changes in physiological and species-interaction effects in the model outputs. Therefore, there is no way to assess changes in competition among the 'new' species mix, nor is there a way to account for whatever gains in water-use efficiency may accompany elevated CO, (Neilson, 1995). Fourth, in a criticism of model-based assessments of climate change effects on forests, Loehle and LeBlanc (1996) note that many forest simulation models assume that tree species occur in all environments where it is possible for them to survive, and that they cannot survive outside the climatic conditions of their current range (fundamental vs. realized niche). The RTA models here reduce this problem by considering a wide range of variables and only trying to evaluate potential range changes due to climate change. These models assume equilibrium conditions, and that there are no barriers to migration. Finally, RTA does have limitations, and spurious or non-causative relationships will appear, especially when RTA methodology is applied to many species without line-tuning for individual species preferences. Improvement of models may be possible for individual species, if individual characteristics and spatial trends are taken into account.

- **STRS**

The SRTS model assumes competitive timber markets. All market models are constructed assuming open competition, even those there is some evidence of (slight) market power in timber markets (Murray, 1995). Distortions are probably minimal relative to other forms of uncertainty, bias, throughout the entire modeling system. Second, the SRTS does not include changes in supply or demand from regions outside of the southern

US. For example, the Pacific Northwestern US has shifted out of timber productivity during the past 10 years. Even if climate change increases forest productivity in this region, the ongoing removal of federal timber from markets suggests that they will not be able to pick up the slack from a drop in southern productivity. Third, the model assumes exclusion of competitive sectors. Relative land returns can have an important impact on how land is allocated between forests and agriculture in the South (Alig, 1986; Hardie and Parks, 1997). Finally, we assume myopic price expectations.

CONCLUSIONS

The linked forest productivity, biodiversity and economic models demonstrated the inherent buffering capacity of forests to environmental change. Despite having inter-annual productivity variation greater than 60%, regional changes in forest growth was low. The increase in mean annual air temperature had little impact on southern pine inventories between 1990 and 2040 (2.5% increase). Beyond 2040, forest productivity is predicted to decrease across the current range of southern pines with a total reduction 6% from historic levels by 2100. However, the potential reduction in productivity does not take into account potential increases in available timber due to northward movement of the southern pine range. Future research should focus on completing the model linkage so that changing productivity across changes in species range can be accumulated for use in economic forest timber supply models.

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