Signal-transfer modeling for regional assessment of forest responses to environmental changes in the southeastern United States

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Stochastic transfer of information in a hierarchy of simulators is offered as a conceptual approach for assessing forest responses to changing climate and air quality across 13 southeastern states of the USA. This assessment approach combines geographic information system and Monte Carlo capabilities with several scales of computer modeling for southern pine species and eastern deciduous forests. Outputs, such as forest production, evapotranspiration and carbon pools, may be compared statistically for alternative equilibrium or transient scenarios providing a statistical basis for decision making in regional assessments.

Keywords: cluster analysis, eastern deciduous forest, geographic information system, global change, Monte Carlo simulation, nitrogen deposition, ozone, scaling up, site index, southern pine forest

1. Introduction

The US Global Change Research Program has identified the need for "regional analyses of the environmental and socio-economic consequences of climate change and other aspects of global change, in the context of other stresses" [1]. Holistic representation of regional forestry that incorporates information at a range of scales requires an integrative modeling framework for incorporating small scale information with regional scale data sources. The challenge of scaling up, i.e., of incorporating small scale responses such as in leaf physiology into larger scale processes of the canopy, stand or ecosystem has been the subject of considerable discussion in recent years (e.g., [2–5]).

Particular concerns in scaling up from physiological to landscape scales are (1) the accounting for relevant processes that control the behavior of the soil–plant–atmosphere system at particular scales, and (2) the transfer and/or transformation of relevant information from one scale to the next. One approach to scaling up involves the transfer of output from a smaller-scale model as input variables in a larger-scale simulator. This signal-transfer modeling approach addresses scaling concerns by (1) explicitly modeling processes at the scale at which they operate and for which empirical information and mechanistic understanding is available, and (2) explicitly transferring control information from one scale to the next in a form that is directly used by the next hierarchical level. We outline an approach for incorporating physiological responses of forests to changing environmental conditions into a regional forest assessment. The approach incorporates signal transfers within a hierarchical modeling structure which allows the whole to provide much more information than the sum of the component contributions.

An alternative assessment approach involves direct simulation of the large scale response (e.g., [6–8]). A challenge with this approach is determining large-scale functional representations that adequately capture relevant small scale processes. Ecosystem-scale forest simulators, for example, usually do not account for tree population dynamics and shifts in species composition. Thus they do not account for a potentially important source of variability in ecosystem response. Luxmoore and Baldocchi [9] noted that tree physiological and forest ecosystem models with functions for atmospheric CO_2 and climate effects generally predetermine a response. In contrast, forest population (succession) models may not show significant long-term responses to CO_2 enrichment or changes in climate, particularly in stands with overriding variability in recruitment and mortality.

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1.1. Signal-transfer modeling

Luxmoore et al. [10] used a signal-transfer approach for scaling up by passing output from a physiological-scale model (Unified Transport Model, UTM) to a forest succession simulator (FORET). The simulated physiological response of an oak-hickory (Quercus-Carya spp.) forest to CO_2 enrichment was passed to FORET as an annual stem wood increment multiplier. This multiplier was applied to the diameter growth equations in FORET. The biomass production at the stand scale showed a CO_2 response for a few decades in FORET simulations. However, after 100 years stochastic variability in the establishment of new individuals and in tree mortality resulted in biomass variability that exceeded the growth increase due to CO_2 enrichment. No significant long-term response to CO_2 enrichment was shown for the oak hickory forest in this modeling study. This is an example of one signal being passed between two simulators for the scaling up of short-term physiological responses to long-term forest stand dynamics.

In another signal-transfer analysis, the potential impact of ambient ozone on loblolly pine (Pinus taeda) plantation lumber yield was evaluated [11] by sequentially passing signals between three models. First, physiological responses to ozone were simulated with the UTM, and a 5.4% decline in annual stem wood increment was obtained with ambient ozone exposure relative to the control case without ozone. This signal was passed to a stand dynamics model, LINKAGES, as a stem wood multiplier and applied to the diameter growth equation in LINKAGES. This signal caused a 5% decline in the mean height of the dominant and codominant trees at a stand age of 25 years. This mean height value is the predicted site index for the loblolly pine stand. This reduced site index signal was passed to a plantation management model, PTAEDA2, and merchantable yield from loblolly pine decreased by 6% over a 35-year rotation as compared to a control simulation. In all cases the lower scale model provided integrated output results in a compatible form for the upper scale modeling algorithms. These ozone impact predictions have not been experimentally verified; however, the simulations provide insights about potentially important ozone effects at several scales. The comparison of results from the two signal-transfer studies outlined above suggests that long-term growth responses to environmental stress in managed plantations (loblolly pine) may be more readily detected than in natural ecosystems (e.g., oak-hickory forest described above) due to reduced variability of establishment (planting) and mortality (harvesting) in managed stands.

1.2. Addressing regional forest issues

Extensive conifer and deciduous forests occur in the southeastern United States. Loblolly pine is the most important commercial species in the region and is dominant in the Piedmont and Coastal Plain physiographic regions. Slash pine (Pinus elliottii) occurs predominantly on the lower Coastal Plain. Several other southern pine species (white, P. strobus; shortleaf, P. echinata; Virginia, P. virginiana; longleaf, P. palustris; sand, P. clausa; pond, P. serotina) also grow in the region. Eastern deciduous forests are dominant in the Appalachian, Cumberland and Ozark mountain areas. A relatively small area of red spruce – Fraser balsam fir (Picea rubens – Abies fraseri) forests occurs in the high elevations (above approximately 1100 m) of the Appalachian mountains. These various forests of the southeastern United States are projected to experience significant environmental changes over the next several decades [12]. Atmospheric CO_2 continues to rise, tropospheric ozone concentrations are increasing in some areas, and nitrogen deposition is projected to increase. In addition climatic conditions could change with warming temperatures, particularly at night, and modified precipitation regimes. All of these possible changes can be evaluated with suitable assessment modeling. We offer an assessment modeling approach that evaluates the effects of the five factors of atmospheric CO_2, N deposition, ozone exposure, temperature and precipitation on forest ecosystems with signal-transfer modeling.

An expansion of earlier signal-transfer modeling is outlined in this report as an approach for assessing regional forest responses to environmental changes. This assessment method is an outgrowth of earlier modeling contributions from the Southern Global Change Program of the USDA Forest Service [12] and the Integrated Forest Study [13] sponsored by the Electric Power Research Institute, Palo Alto, California. Modeling components from these two programs are an extensive resource, and when combined with GIS databases and Monte Carlo methods form a coordinated framework for regional forest assessment. We use the 13 southeastern states of the United States from Virginia and Kentucky to Florida and from North and South Carolina to Oklahoma and Texas as the assessment region.

First, we provide an overview of the signal-transfer method of regional assessment as a framework for relating further details about the method. Three modules are used for assessing the effects of multiple environmental stresses on forests in a large heterogeneous region as follows:

(I) *Signal response modeling*: This module consists of computer models that simulate the effects of combinations of five environmental factors on short time scale ecophysiological processes through to an annual stem wood increment response. These tree responses are stored in five-dimensional response surfaces developed for each of three dominant forest types (loblolly pine, slash pine, eastern deciduous forest). The response surfaces are accessed by a stand dynamics model (LINKAGES) in the third module. We also incorporate Monte Carlo simulation in module I by propagating frequency distributions (rather than mean values) through each simulator providing annual stem wood increment signals as frequency distributions.

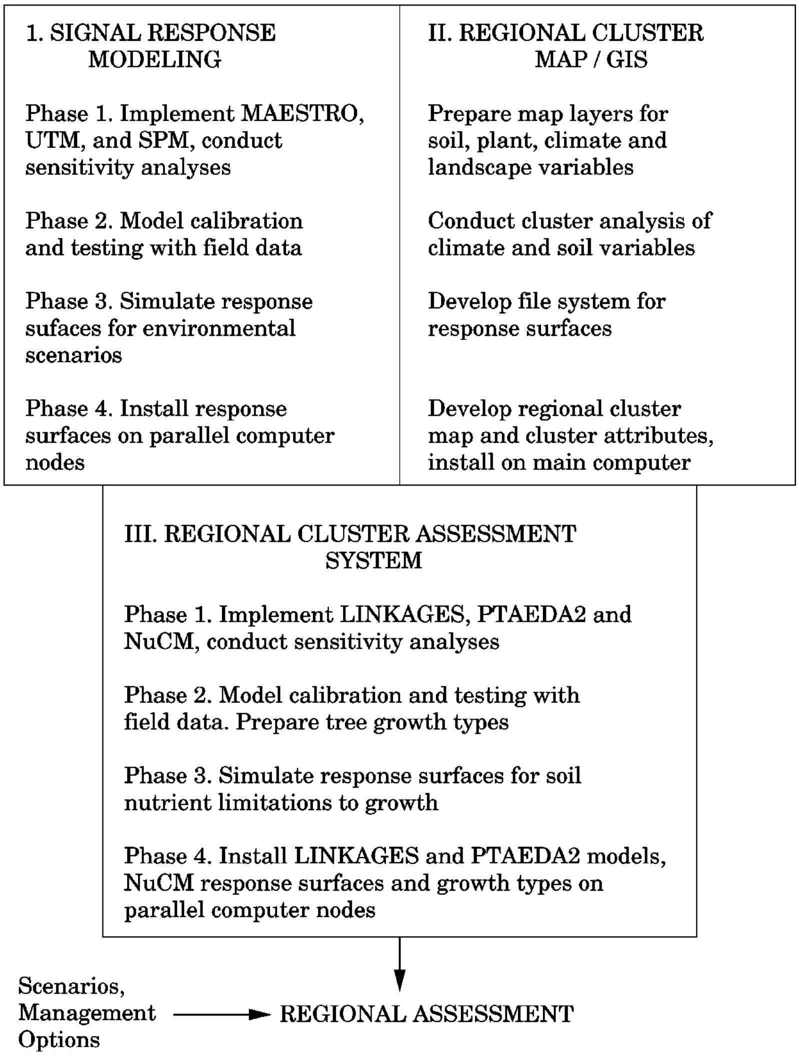


Figure 1. Four phases of development of the linked dynamic model (module I) combine with the development of the geographic information system (module II) to develop information that enters module III for regional assessment applications.

(II) *Regional cluster map/GIS*: The 13-state region is divided into clusters with similar soil, landscape and climatic attributes. A multivariate clustering technique is applied within the 78 major land resource areas described by the Natural Resources Conservation Service, USDA for the 13-state region. We prepare about 1000 clusters across the assessment region. Frequency distributions of soil, landscape and climatic attributes required for stochastic simulation with LINKAGES in module III are determined for each cluster.

(III) *Regional cluster assessment system*: Regional assessment is undertaken with three calibrated versions of LINKAGES for simulation of loblolly pine, slash pine and eastern deciduous forest for periods of several decades. For a particular scenario of environmental change LINKAGES accesses the previously determined forest-specific response surfaces (module I) and the appropriate signal for the selected scenario is determined. LINKAGES is applied to each of the clusters in the regional cluster map using Monte Carlo simulation. The cluster results are aggregated to give a regional assessment, and alternative scenarios may be statistically compared.

These three modules (figure 1) are designed for assessment of coniferous and deciduous forest responses to selected combinations of climate and air quality changes. The modeling focuses on the three dominant forest types in the southeastern region (loblolly pine, slash pine and eastern deciduous forest) and also provides inferential assessments for other southern pines (shortleaf pine, sand pine, pond pine, Virginia pine, longleaf pine) determined from the responses of loblolly pine. The features of the three modules are outlined in the next three sections.

2. Module I: Signal response modeling

Signal response modeling involves two simulators (UTM, SPM) that propagate the ecophysiological responses of trees to climate and air quality to the forest stand scale. The UTM applies a big-leaf algorithm for calculation of net photosynthesis, and prior to its use in assessment simulations the code is calibrated with a detailed forest canopy model (MAESTRO). This calibration adjusts the UTM for self shading of leaves as leaf area index increases. The UTM is next calibrated for simulation of loblolly pine and eastern deciduous forest stands. The SPM is currently the best available simulator for ecophysiological processes of slash pine.

Each simulator is executed many times with Monte Carlo simulation using the mean and variance of input variables to generate frequency distributions of output signal responses. Monte Carlo simulation are conducted with an efficient Latin hypercube sampling method [14,15]. In particular, stochastic modeling of tree physiological responses to selected combinations of temperature, precipitation, nitrogen deposition, atmospheric CO_2 and tropospheric ozone exposure generates frequency distributions of a stem wood multiplier which are stored in response surfaces for each of the three forest types (slash pine, loblolly pine, eastern deciduous forest). These response surfaces are the "archived memory" from the physiological simulators. Use of response surfaces avoids the need to continually use physiological models in regional assessment simulations and allows flexible consideration of either equilibrium or transient scenarios. Signals are selected or interpolated from these response surfaces as needed and passed to the LINKAGES model in regional assessment simulations (see module III).

The three codes, MAESTRO, UTM, SPM, used in signal response modeling (figure 1) at the ecophysiological scale are well established simulators, each being developed over many years and tested in a range of applications. The following gives brief descriptions of the codes and the signals transferred in the modeling hierarchy:

2.1. MAESTRO – canopy processes model

MAESTRO is a physiological process model [16] that calculates the irradiance distribution in canopy volumes of a target tree in a stand and determines carbon gain using hourly time-step calculations of canopy conductance, photosynthesis and respiration. A loblolly pine version of MAESTRO [17] has been modified with enhanced canopy shape attributes [18]. MAESTRO is specifically used for calibration of a big leaf algorithm for net carbon fixation in the UTM. This is achieved with a calibration function that adjusts for the effects of foliar self shading on canopy photosynthesis that are included in MAESTRO but are not part of the big leaf model. This function is obtained for a range of leaf area index values [19].

2.2. UTM – water, carbon and chemical coupled-processes model

The unified transport model (UTM) is a linkage of five component models [20] for simulation of water, carbon and solute (nutrient and pollutant) transport of a soil–plant system. Simulations are conducted with hourly time steps except during precipitation when 15 min time steps are used. Translocation is driven by sucrose gradients using a source–sink framework which results in dynamic carbon allocation associated with differing photosynthetic (insensitive) and plant growth (sensitive) responses to stress [21]. The model was applied to nitrogen dynamics in an oak-hickory forest [22], and algorithms for ozone impacts on foliar processes and growth of loblolly pine have been incorporated [11]. Two versions of the UTM (loblolly pine, deciduous forest) are used for evaluating climate change and air quality effects on annual net carbon gain and carbohydrate storage of stems. These variables are stored in forest-specific response surfaces as stem growth multipliers that can be transferred to LINKAGES (loblolly pine, deciduous forest versions) simulations for alternative scenarios.

2.3. SPM – slash pine carbon dynamics model

The slash pine model (SPM, [23]) generates seasonal ecosystem-level carbon budgets for slash pine forest stands [24]. This simulator has been used for investigation of fertilization and climate change effects on Florida slash pine stands [25]. The canopy is divided into nine vertical layers with a vertical distribution of relative gap frequencies that produces a realistic light environment. The processes simulated are net canopy assimilation, maintenance respiration, growth respiration, carbon partitioning (growth), soil CO_2 evolution, decomposition and mortality. The model is parameterized and tested for a typical coastal plain pine flatwoods site in north-central Florida, and is used for evaluating climate change effects on annual net carbon gain and carbohydrate storage of slash pine stems. Ozone effects are not undertaken for slash pine assessments. Simulated growth responses are stored in a slash pine specific response surface as stem growth multipliers representing integrated environmental response signals. These signals are transferred to LINKAGES (slash pine version) for assessment simulations with module III.

3. Module II: Regional cluster map/GIS (RCM)

The second module of the regional assessment approach involves a raster (pixel) based GIS for importing and managing geographically distributed information for the 13 southeastern states (figure 1). Model inputs are managed and mapped at the resolution of the data source in the GIS data layers. Most files are mapped at a raster size of 1 km^2. The public domain GRASS GIS software is used throughout. All map products are projected in Lambert azimuthal equal area format. However, these maps may be readily converted into alternative projections or into the format of other GIS software, as needed. The GIS module is used for three main purposes: to develop a regional cluster map, provide input data for simulations with LINKAGES and to map assessment results. An outline of the GIS data sources is given along with their use in developing a regional cluster map as the spatial basis for regional assessments. The clustering procedure aggregates rasters into groups that have similar ranges of attribute variability. Even though spatial resolution is not maintained within each cluster, the data attributes contributing to each cluster are included in the assessment by Monte Carlo simulation.

3.1. GIS information sources

The geographic data used in assessment modeling and for model testing are available in a variety of formats (vector, raster and point data) for the southeastern United States. The spatial resolution of these databases also varies, from relatively coarse 0.5 degree to relatively fine (3.0 second) digital elevation data. The GIS is used to integrate these diverse databases into a common and consistent geo-referenced (coregistered) framework. We use Internet sources for some of these data and list the Internet address for reference. The primary data sources in the GIS include:

(1) Topography. A digital elevation model (DEM) of the southeastern US. The DEM is based on 3.0 second data from the US Geological Survey (USGS).
http://edcwww.cr.usgs.gov/landdaac/gtopo30/gtopo30.html

(2) Contemporary landcover. The USGS Eros Data Center AVHRR-NDVI landcover product [26] is used to define the contemporary distribution of vegetation and landcover.
http://edcwww.cr.usgs.gov/landdaac/glcc/tablambert_na.html
Mid summer (11–31 July) leaf area maps have been prepared by Dr. Ned Nikolov (Oak Ridge National Lab) from 8 km AVHRR multispectral data obtained during 1991–1994 by the NOAA/NASA Pathfinder Program.

(3) Soils. Soil type, texture, depth and other properties are defined by the Natural Resources Conservation Service STATSGO database [27]. The National Soils Characterization Database (NSCD) provide empirical data for many soil attributes. The combination of NSCD and STATSGO is used to develop 1 km raster maps of soil properties needed in assessment modeling.

(4) Contemporary climate. Mean minimum and maximum temperatures from monthly station normals for the period 1961–1990 [28] and mean monthly precipitation data from [29] are used to define contemporary climate.
http://cdiac.esd.ornl.gov/ftp/ndp019r3/ (HCN)
http://www.ncdc.noaa.gov/ol/climate/research/ushcn/ushcn.html (HCN)
ftp://www.ncdc.noaa.gov/pub/data/normals/ (NCDC normals)
http://www.ocs.orst.edu/prism/prism_new.html (orographically adjusted precipitation)
http://daac.gsfc.nasa.gov/CAMPAIGN_DOCS/FTP_SITE/INT_DIS/readmes/srfrad.html(#501 NASA GISS solar insolation)

(5) Projected climate. We use the climate scenarios of the VEMAP dataset [30] to define changes in climate for the southeastern US from present to 2100.
http://www.cgd.ucar.edu:80/vemap/

(6) Forest distribution, composition, productivity and structure. Databases maintained by the resource planning assessment (RPA) and forest inventory and analysis (FIA) of the US Forest Service are used to define the contemporary forest distribution and condition of commercial forests across the southeastern US. Delcourt et al. [31] provide additional information.
http://www.srsfia.usfs.msstate.edu/ (FIA for southeastern US)
http://www.epa.gov/docs/grd/forest_inventory/ (RPA)

(7) NASA Distributed Active Archive Centers (DAAC) are future sources for remote sensing data, e.g., Earth Observing System data and ground-based biomass data. The DAAC at Oak Ridge National Laboratory is a convenient source for biogeochemical dynamics and net primary production data.
http://www-eosdis.ornl.gov/npp/npp_home.html (NPP)

(8) The Carbon Dioxide Information Analysis Center (CDIAC) at ORNL provides extensive climate and atmospheric data including linkage to the AmeriFlux data from eddy covariance monitoring sites.
http://cdiac.esd.ornl.gov/ (CDIAC)
http://www.esd.ornl.gov/programs/NIGEC/ (AmeriFlux)

3.2. Multivariate clustering

The 13-state region of the southeastern United States contains about 2.2 million km^2. Soil, vegetation, climate and landscape attributes needed for modeling with LINKAGES are assembled for each km^2 in the region. However, assessment calculations are not performed at this spatial resolution. Instead, we use a spatial multivariate clustering technique to empirically divide the southeastern region into a number of geographic clusters with relatively homogeneous attributes (figure 2). Attribute data for each of the 2.2 million cells are used as coordinates in N-dimensional data space for mapping the identity of the geographic locations. An iterative procedure defines clouds or clusters of geographic locations with relatively similar attributes. These clusters are reassembled in geographic space with each raster coded with its cluster assignment [32,33].

This geographic multivariate clustering is implemented with nine GIS attribute maps: elevation, soil available water holding capacity, soil organic matter, soil nitrogen, seasonally high water table depth, mean solar insolation during the growing season, mean precipitation during the growing season, heat degree day sum during the growing season, and cold degree day sum during the non-growing season. In addition, a physiographic constraint is imposed. We use the 78 major land resource areas (MLRAs, [34]) within the

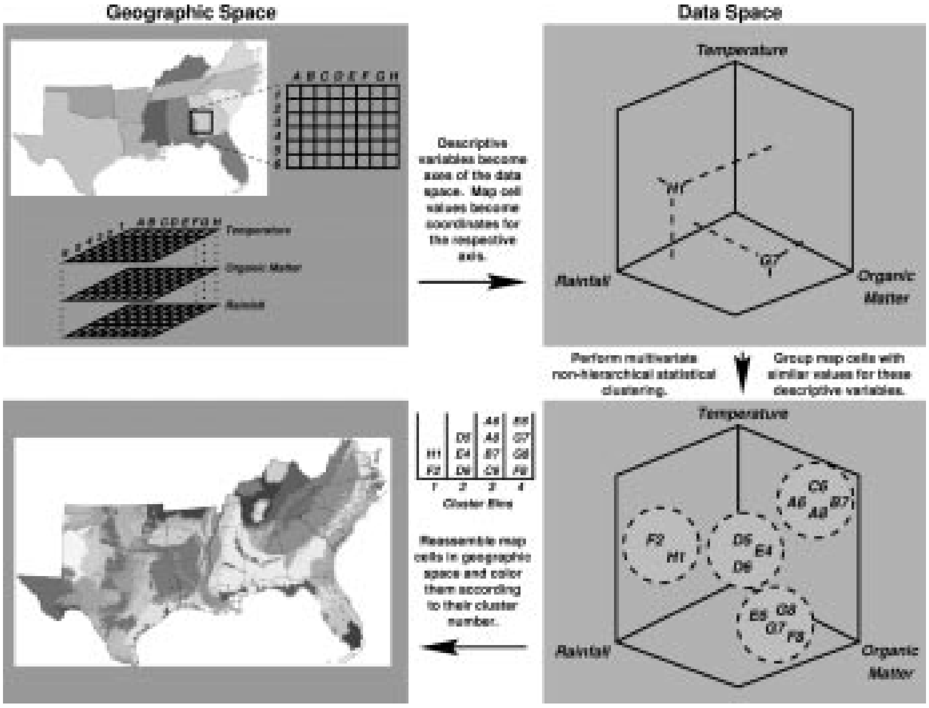
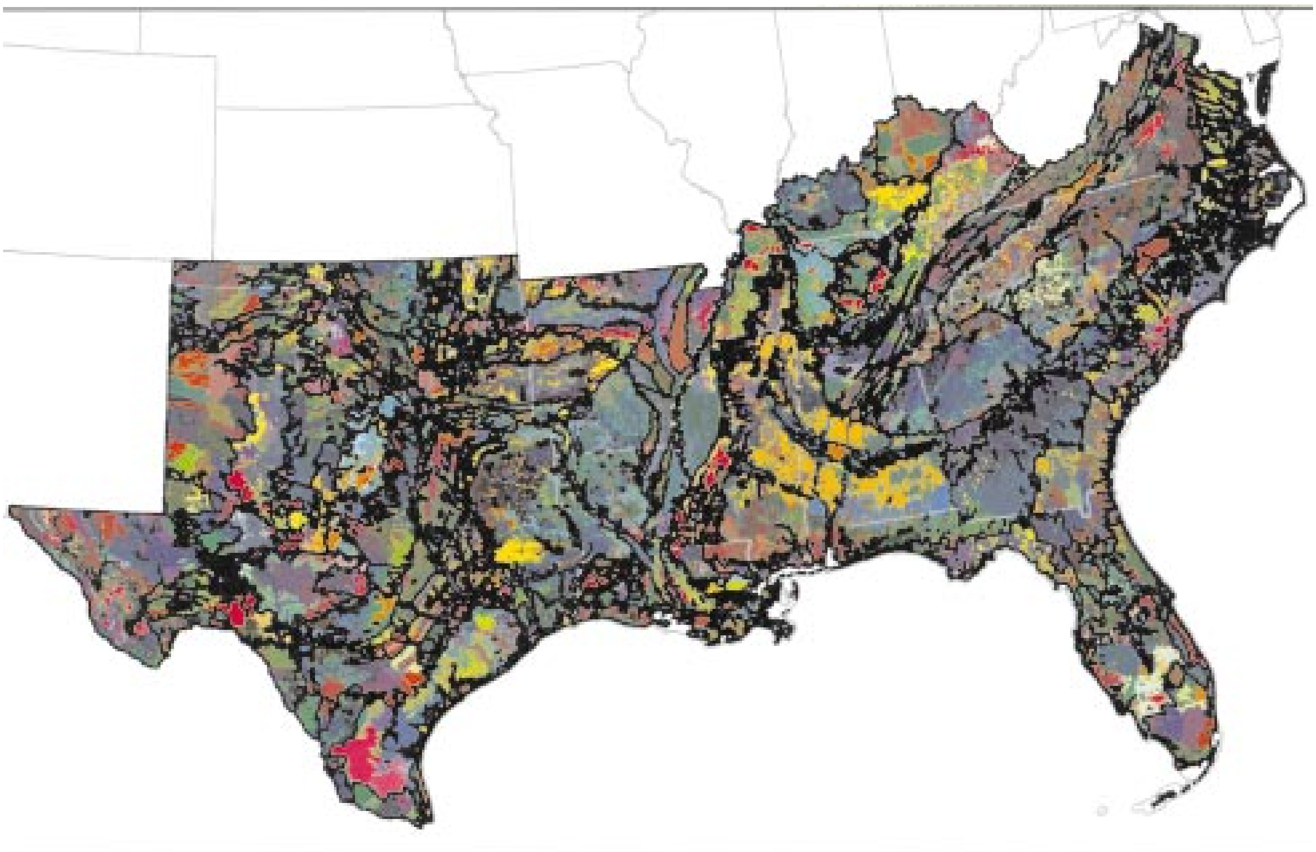


Figure 2. Nine selected data layers (only three shown), important in the annual cycle of forest growth, are aggregated by multivariate statistical analysis applied in data space and these aggregates are reconstituted as spatial clusters in geographic space. All clusters are determined within the major land resource areas (physiographic regions) of the 13 southeastern states. Each cluster has similar combined variability of soil, plant, climate and landscape attributes.



13-state region as templates within which the geographic clustering is performed. The MLRAs are physiographic regions determined by the Natural Resources Conservation Service, USDA, and these are provided in the STATSGO database for GIS applications.

To ensure similar within-cluster variance across MLRAs, clusters are defined using a specified radius size in the data space defined by the attribute values. The size of this radius determines the number of clusters generated. Use of the 78 MLRA templates allows the multivariate geographic clustering to be undertaken in 78 separate analysis steps with the same data-space radius.

A regional cluster map with 1061 clusters is generated with this technique (figure 3). Some clusters are not spatially contiguous, however, most clusters form largely contiguous and homogeneous patches. Cluster sizes vary and follow an approximately lognormal distribution with the smallest cluster being 50 km^2 and the largest having an area of 29,050 km^2. Clusters smaller than 50 km^2 are aggregated into neighboring clusters. The GIS attributes for all cells within each cluster required for simulation with LINKAGES (e.g., soil organic matter, soil nitrogen, soil water storage) are statistically summarized for each map layer as a mean, standard deviation, minimum, maximum and distribution type (e.g., normal, lognormal). These particular attributes are a subset of the attributes used for determining the regional cluster map. The geographic clusters define the spatial basis for the regional assessment. Within any cluster, there is no spatial discrimination; however, the variability of attributes within a cluster is preserved in a frequency distribution and incorporated into regional assessments using Monte Carlo simulation by the Latin hypercube sampling method [21].

4. Module III: Regional cluster assessment system (RCLASS)

The third module provides regional assessments of southeastern forests in relation to environmental changes. Assessment simulations may be conducted with equilibrium or transient scenarios for the 13-state region by using fixed or temporally varying values from the module I response surfaces, respectively. RCLASS uses three models (LINKAGES, NuCM, PTAEDA2) and empirical tree growth data (figure 1). These components are briefly described.

Figure 3. Regional cluster map for 13 southeastern states with 1061 clusters is shown in random colors. Clusters are developed within 78 major land resource areas (black boundaries) thus preserving established physiographic features of the region. Clusters range in size from 50 to over 29,000 km^2. The 1 km^2 raster attributes required for LINKAGES simulation are summarized for each cluster as a mean and standard deviation for use in Monte Carlo simulation by Latin hypercube sampling.

4.1. LINKAGES – forest stand development and productivity model

LINKAGES is an individual based stand model (gap model, [35]) that simulates establishment, diameter and height growth and mortality of trees with an annual time-step for a forest community on “gap” areas of 0.1 ha. The code simulates carbon, water and nitrogen dynamics of mixed genotype, mixed-species or mixed-age class forest stands of eastern North America [36,37]. Nitrogen cycling partially controls tree growth, the rate of organic matter production and species composition through competition for available nitrogen. In turn, available nitrogen depends on the amount and quality of organic matter produced. Water budget calculations determine soil water effects on growth as well as stand evapotranspiration. LINKAGES is used to simulate productivity of three forest types (slash pine, loblolly pine, deciduous forest versions of the code) in all regional assessments. In the case of loblolly pine, changes in site index (average height of dominant and co-dominant trees at age 25 years) are estimated as signals for transfer to the PTAEDA2 plantation management model. In addition, average tree heights at two ages are selected from LINKAGES output for loblolly pine to identify height growth types by the two-point method of Zeide [38].

4.2. NuCM – soil chemical processes and nutrient cycling model

The nutrient cycling model (NuCM) was developed as part of the Electric Power Research Institute’s Integrated Forest Study [39] to simulate the effects of atmospheric deposition and forest management practices (harvesting, liming, fire) on growth and nutrient cycling of a forest stand. Calculation of nutrient availability is determined by soil chemical processes including mineralization, chemical exchange, solubility and mineral weathering. Outputs include forest growth, annual nutrient budgets, and weekly (or monthly) mean chemical concentrations in throughfall, soil and soil solution. The model successfully simulated the effects of changing atmospheric deposition [40,41], liming [42] and harvesting [43]. The model has been calibrated for a red spruce site in the Great Smoky mountains, NC [40], a mixed deciduous forest at Coweeta, NC [41], a loblolly pine site at Duke Forest, NC and mixed deciduous forest sites at Coweeta, NC and Walker Branch, TN [43,44].

The maximum biomass vs. stand age relationships for the dominant soil types of the southeastern region with soil nutrient limitations (e.g., P, K, but not N which is included in LINKAGES simulations) are predetermined with NuCM. These results are stored in a response surface for a range of temperature, precipitation and atmospheric CO_2 conditions and are used to constrain forest growth simulations in assessments with LINKAGES. In a given assessment scenario, simulated forest growth vs. time results from LINKAGES are compared with the NuCM nutrient-limited growth predictions appropriate for the soil type involved.

If NuCM predicts less forest growth than LINKAGES for nutrient deficient (excluding N) soils then the lesser value is used in ongoing assessment calculations.

4.3. PTAEDA2 – loblolly pine plantation management model

PTAEDA2 is a distance-dependent, individual tree, growth and yield model for loblolly pine that simulates a plantation from the time of planting through a desired rotation using annual time steps [45]. Trees are assigned coordinate locations in a stand, and annual growth is determined as a function of tree size, site index and competition from neighbors. Mortality is simulated with a stochastic variable and by competitive relationships determined in part by vertical canopy thickness as a proportion of tree height (crown ratio). Subroutines for hardwood competition, stand thinning and fertilization also determine tree and stand development. The mensuration data used to develop the empirical relationships in PTAEDA2 come from a wide range of loblolly stands distributed through the southeastern US [46,47]. Site index is the primary input variable determining environmental effects on plantation growth. We provide simulated site index values from LINKAGES for assessing climate change and air quality effects on managed loblolly plantations. Simulation of plantation management options (planting density, thinning, weed control, fertilization) in loblolly pine stands may be explored as adaptations to changing environmental conditions.

4.4. Tree growth types – height vs. age functions

A growth type of a forest stand is defined by mean tree height of dominant and codominant trees at two selected ages [48–50]. This is an enhancement of the height at one index age which defines site index. Growth types define stand height growth patterns more accurately than site index by allowing different height growth patterns for the same site index value as is observed in comparisons of naturally regenerated and managed stands. Height growth types have been constructed for southern pine species by distilling growth patterns from a large number of empirical tree height/age relationships represented in 436 published site index curves [38].

Growth types are used in regional assessments in two steps to estimate environmental change responses of pine species that are not specifically simulated. First, the height of loblolly pine from LINKAGES simulations at two ages (15, 40 years) for a given environmental scenario are determined and matched with the empirical growth types [38] to identify the growth type corresponding to the simulated loblolly pine stand. In the second step, empirical relationships between loblolly pine growth type and the associated growth types for other southern pine species (Zeide, personal communication) are used to infer the responses of these other pine species based on the simulated growth type for loblolly pine. This is feasible since loblolly pine grows in a wide range of areas where shortleaf pine, Virginia pine, sand pine, pond pine and longleaf pine also grow. The use of growth type associations allows the scope of an assessment to be expanded inferentially to a broad range of southern pine species without undertaking species-specific simulations.

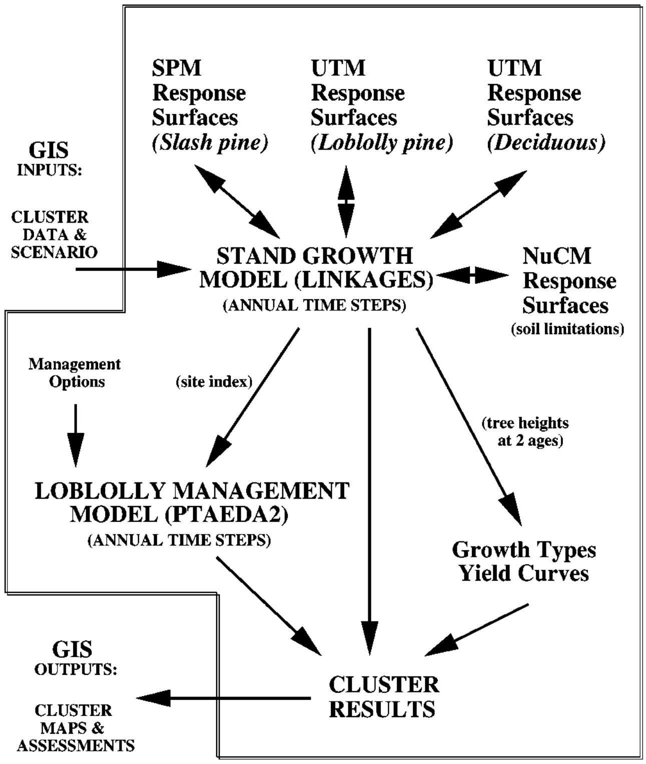


Figure 4. Each node of a parallel computer receives the response surfaces for three forest types (from SPM and UTM), the response surface from NuCM for nutrient deficient soils, the LINKAGES and PTAEDA2 codes, and the tree growth types (shown within the bounded area). Input data and scenario information for each spatial cluster of the region are sequentially provided to computer nodes by the central processing unit. Outputs from each cluster are combined into maps displaying regional assessment results.

5. Development and implementation

The development of the signal-transfer assessment method with the above three modules involves four phases (figure 1) for:

(1) Implementing all simulation models onto a common computer platform, combining each with the PRISM code [15] for sensitivity analyses to determine sensitive variables and for setting up the models for Monte Carlo simulation by the Latin hypercube sampling method;

(2) Calibrating and testing all models with field data from the region, and assembling the Zeide growth types for southern pine species and their relationships with loblolly pine growth types;

(3) Running SPM (slash pine) and UTM (loblolly pine, deciduous forest versions) for a range of climate and air

quality scenarios with Monte Carlo simulation to develop response surfaces that encompass the past, current, and anticipated future environmental conditions, and run NuCM to develop biomass vs. time patterns for the soil types with nutrient deficiency (except N) in the region; and

(4) Installing the response surfaces for the three forest types, the NuCM response surfaces for soil limitations to growth and the Zeide growth types [38] onto each node of a parallel processing computer system for assessment calculations with LINKAGES and PTAEDA2 (figure 4).

All simulations conducted in phases 3 and 4 are made with Monte Carlo simulation for determination of frequency distributions of sensitive input variables (insensitive variables are given mean values only) needed in Latin hypercube sampling. Any component code of the signal transfer assessment method in modules I and III may be upgraded as new scientific information becomes available. Additionally, any simulator may be replaced with a suitable alternative. These changes may require revision of the response surface results.

5.1. Response surface interpolation

Output distributions of signal responses generated in phase 3 from each simulator in modules I and III are stored in five-space hypervolume response surfaces for up to five environmental factors (temperature, precipitation, CO_2, O_3, nitrogen deposition) using a machine-independent file format. The NCView public domain file format is used for file management and display of all response surfaces.

All possible combinations of the five environmental conditions are not explicitly simulated with the ecophysiological (SPM, UTM) models in the signal response modeling. Rather, the five-dimensional hypervolume response surfaces representing all possible environmental conditions are sparsely populated with explicit simulation results from these two codes for the three forest types. These hypervolume response surfaces are interpolated during RCLASS simulations with a five-dimensional interpolation tool [51] to obtain response values for environmental conditions which are not specifically simulated. This interpolation technique embraces the multivariate nature of environmental factors and the technique is appropriate where simulated responses to varying environmental conditions change smoothly. The nearest-neighbor technique associated with the Modified Quadratic Shepard's method [52] has been adapted and extended to conduct five-dimensional interpolation with sufficient accuracy [51]. In this assessment approach, files of simulation results are called simabases to distinguish modeling results from databases derived from instrumental measurements and calibrated data sources [53].

5.2. RCLASS applications

The regional cluster assessment system applies the signal-transfer assessment method (figures 1 and 4) to the attributes of each cluster in the regional cluster map (figure 3) for particular combinations (scenarios) of up to five environmental conditions (atmospheric CO_2, N deposition, temperature, precipitation and tropospheric ozone exposure) that are projected to change over the next several decades. Calibrated versions of the LINKAGES model are used for simulation of each cluster of the region for loblolly pine, slash pine, and/or eastern deciduous forest as appropriate. In loblolly pine plantation applications, the PTAEDA2 management model uses site index predictions from LINKAGES to determine scenario impacts on plantation productivity. Adjustments in loblolly pine plantation management (e.g., planting density, fertilization, weed control) are simulated with PTAEDA2 as adaptations to the altered environmental conditions. The signal transfers to PTAEDA2 (site index) and the Zeide growth types (tree heights at two ages) for loblolly pine assessment scenarios do not require response surface look up since these signals are calculated directly in each scenario.

The sensitive input variables for LINKAGES are sequentially provided as mean, standard deviation, frequency distribution type, and maximum and minimum values for each cluster of the RCM (figure 4). Latin hypercube sampling of these distributions generates input data sets for LINKAGES applications. Monte Carlo simulation with these input data sets generates predicted forest responses in each cluster which are summarized as a distribution type, mean, standard deviation, and the maximum and minimum values for each output. The whole process is repeated for additional combinations (scenarios) of the five environmental conditions.

Compilation and mapping of output results from all clusters gives a regional mean and variance which provides a basis for statistical comparisons among alternative scenarios on a cluster or whole region basis. Cluster mean and variance maps are produced for selected output variables under any desired combination of equilibrium or transient environmental conditions.

6. Hierarchical constraints on signal propagation

All regional assessment modeling approaches seek to provide intelligence, where intelligence is the ability to catch the essential features resulting from complex processes, information, and data. Our use of a hierarchy of simulators with signal transfer constrains signal propagation within algorithms represented in each simulator at each particular scale. Thus, the signal-transfer approach results in a lower scale signal being constrained within the modeling structure of the upper scale, thus constraining aberrant error propagation [19].

Potentially beneficial effects of global change or detrimental effects from decline in air quality on forests may

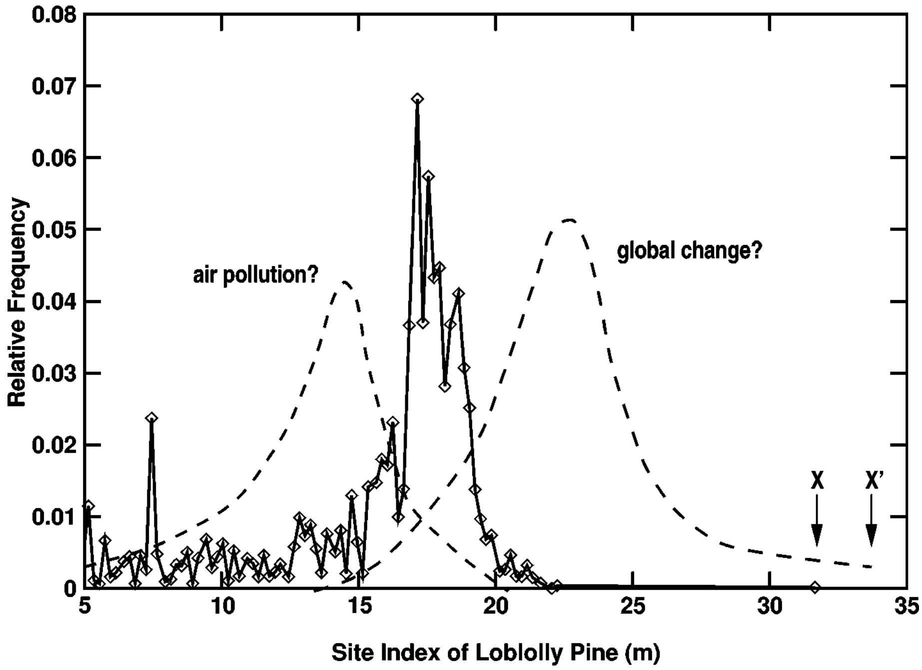


Figure 5. Frequency distribution of site index (base age 25 years) for loblolly pine in the southeastern region of the United States derived from STATSGO shown with hypothesized shifts due to air pollution and global change effects. The zone marked X–X′ represents predicted increases in site index beyond the known empirical database. The figure shows the expectation that future environmental change will not in general exceed the empirical information provided by the existing wide range of conditions already known for the region.

lead to shifts in site index, shown hypothetically in figure 5, relative to the current frequency distribution for the southeastern United States. The frequency distribution of current site index (adjusted to an index age of 25 years) for loblolly pine (figure 5) is derived from a map of site index values obtained from the STATSGO database with an index age of 50 years [27]. Environmental change scenarios are expected to cause shifts in the frequency distributions of site index as land quality is predicted to change spatially across the region. It is possible in signal-transfer modeling to predict site index values in excess of the current maximum value (shown by zone X–X′ in figure 5). Such outcomes may occur for a small proportion of cases. The broad range of extant variability in the southeastern region is expected to be rearranged spatially in alternative simulation scenarios. Statistical tests of output frequency distributions may be used to identify scenarios that cause significant forest changes relative to the inherent variability of current conditions.

6.1. Landscape processes and future research needs

Several important processes have spatial extent as a fundamental component of their operation, including changing land use, invasion of pests (e.g., chestnut blight, gypsy moth) at regional scales, and forest fires at subregional and water-shed scales. Landscape-scale ecological processes may be simulated with cellular automaton epidemic models as nested applications within the cluster structure of the RCM. The appropriate spatial resolution of a nested application is determined by the specific landscape process. For example, cellular automaton models have been applied to wildfires in Yellowstone National Park with 30 m pixels [54] and with 90 m pixels in land use change predictions for the Little Tennessee River Basin in North Carolina [55]. For each landscape process, the future state of a landscape unit depends on its current state, the states of its neighbors and their spatial separation distances. Transition rules and transition probabilities, which stochastically describe the new state of the unit as a function of surrounding conditions, must be predetermined by empirical analysis or modeling [56].

Land use change simulation may be undertaken with LUCAS, a multidisciplinary simulation environment for the investigation of land cover and land use change [57]. Conversion from one land cover to another (in sequential time steps) is spatially determined by transition probabilities determined from nonlinear regression models of historical data [58,59]. These probabilities incorporate raster attributes such as slope, elevation, population density, distance to road and distance to market. LUCAS combines both socioeconomic (e.g., land ownership) and ecological factors into the computation of land cover change through the use of multinomial logit models. In order to facilitate the use of independent replicates needed for stochastic simulations, a parallel/distributed implementation of LUCAS on a network of workstations (pLUCAS) has been developed [60]. Land use modeling may be applied on a case by case basis as nested simulations for areas with smaller spatial resolution than that provided in the regional cluster map. Future conditions of land quality for tree growth (site index) in response to environmental change predicted from RCLASS may be incorporated into LUCAS land use change assessments. Hardie and Parks [61] have shown that land quality (land productivity class) is an important determinant of future land use.

Signal-transfer modeling has been pragmatically applied in completed studies and similar practical choices are described in the present framework (figure 4) through the selection of rather few variables to pass between simulator scales. If the approach could be developed with completely new models at all scales, then key questions of what variables to transfer between simulator scales could be addressed without the constraints imposed by existing model structures. However, it is unlikely that totally new model developments will be widely different from current codes. Modification of current model structures, to facilitate the transfer of an expanded number of variables between models, could be attempted if a coherent rationale is developed. This may be needed in assessment applications involving alternative stressors or in applications with other forest species.

Feedback processes operate within each modeling scale in the signal-transfer method, however, there may be need for feedback regulation between modeling scales in some applications. In such cases it would be appropriate to choose a comprehensive model that incorporates the feedback regulation within one model structure. Implementation of feedback regulation from a larger scale to a smaller scale is likely to be cumbersome with our signal transfer approach. A mechanistically based rationale for signal-transfer modeling and future research needs will be aided once the limitations of the scheme proposed in this report have been explored.

7. Summary

A signal-transfer technique for scaling-up results through a hierarchy of simulators is proposed for the assessment of forest responses to changing climate and air quality across 13 southeastern states of the United States. Computer simulations are combined with geographic information system (GIS) capability. We develop information transfer between established ecophysiological models (MAESTRO, UTM, SPM) and models of stand productivity (LINKAGES), soil nutrient dynamics (NuCM) and plantation management (PTAEDA2). Selected results (response signal) are passed between two modeling scales as a mean and variance for application of Monte Carlo simulation. Latin hypercube sampling is used for Monte Carlo simulation to propagate variability of soil and plant inputs through the models. Ecophysiological simulations are generated for combinations of up to five environmental conditions (atmospheric CO_2, ozone exposure, nitrogen deposition, temperature, precipitation) across ranges representative of past, current and anticipated future environmental conditions throughout the southeastern region. These response signals are stored in five-dimensional hypervolume response surfaces.

In this signal-transfer approach tree (e.g., loblolly pine) responses to multiple environmental stresses are simulated with an ecophysiological model to generate stem wood increment responses (tree ring) which are passed to LINKAGES as a normalized multiplier for modification of tree diameter calculations. LINKAGES simulates tree height as a function of stand age for the selected forest type. The mean height of dominant and codominant trees at an index age of 25 years (site index) incorporates stress impacts, and this value is passed to PTAEDA2 for simulation of impacts on loblolly pine plantation yield. In this method, site index is a dynamic integrator of multiple environmental stresses.

GIS databases are assembled for plant, soil and climate attributes for each of the 2.2 million km^2 grid cells of the southeastern region. Geographic multivariate clustering on selected attributes within physiographic major land resource areas produces approximately 1000 spatial clusters, each with relatively uniform attributes. Forest responses are simulated with LINKAGES by Monte Carlo simulation for each cluster with selected combinations (scenarios) of the five environmental conditions using the regional cluster assessment system. These computations are undertaken on a parallel network of workstation computers. Combinations of environmental conditions not explicitly stored in the five-dimensional hypervolume are interpolated multidimensionally, allowing regional assessments for any equilibrium or transient scenario involving combinations of the five environmental conditions.

Regional assessments may be developed for southern pine species and eastern deciduous forests. The use of Monte Carlo simulation throughout the modeling propagates frequency distributions of outputs through the modeling scales, providing a statistical basis for decision making in regional assessments. Forest production, evapotranspiration, carbon storage, and other outputs may be compared statistically for alternative scenarios. Additionally, the consequence of various mitigation and management strategies may be statistically evaluated.

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