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Addressing multi-use issues in sustainable forest management with signal-transfer modeling

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Abstract

Management decisions concerning impacts of projected changes in environmental and social conditions on multi-use forest products and services, such as productivity, water supply or carbon sequestration, may be facilitated with signal-transfer modeling. This simulation method utilizes a hierarchy of simulators in which the integrated responses (signals) from smaller-scale process models are transferred and incorporated into the algorithms of larger spatial- and temporal-scale models of ecological and economic phenomena. Several innovative procedures germane to multi-issue sustainable forest management have been initiated in our signal-transfer modeling development for forests of the southeastern United States. These developments include response surface interpolation for multi-factor signal-transfer, use of loblolly pine modeling to infer the growth of other southern pines, determination of soil nutrient limitations to productivity, multivariate clustering as a spatial basis for defining land units relevant to forest management, and variance propagation through the modeling hierarchy. Algorithms for larger scale phenomena are shown to constrain the variance introduced from a smaller-scale in a simulation of ambient ozone exposure effects on loblolly pine timber yield. Outputs of forest variables are frequency distributions that may be statistically compared for alternative environmental or management scenarios. Published by Elsevier Science B.V.

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1. Introduction

The definition of *sustainable forest management* in quantitative terms is challenging, however, there is recognition that management of forests for a wide

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range of resources and services needs to be conducted in a manner that preserves or enhances the life-sustaining qualities of these ecosystems. Determination of criteria, indices and verifiers for sustainability have been proposed (e.g., Stork et al., 1997), and conferences have been held to obtain various perspectives about sustainability (e.g., Flinn et al., 1998). Sustainable forest management of public and private lands increasingly concerns multi-use issues such as biodiversity, wildlife habitat and municipal water supply in addition to sustainable productivity. How should forests be sustainably managed with changing environmental conditions, variable soil types and topography, a dynamic economic environment and changing public aesthetic values? Evaluation of such multi-use and multi-scale issues may be facilitated with a hierarchy of simulators in which results (signals) from smaller-scale process models are transferred and used in larger spatial- and temporal-scale models of ecological and economic phenomena. This is the basic concept of signal-transfer modeling.

In the management of human systems, such as regional reserves of a consumable resource (e.g., gasoline or fuel oil), planning is made for predictable changes (e.g., holiday travel, seasonal weather changes); however, less predictable changes (e.g., cold snap) can cause supply problems. Quantification of temporal changes in fuel demand is incorporated as information in management of regional fuel reserves, and these vary spatially from region to region. In the case of trees and forests, information transfer across increasing temporal scales provides the means for incorporating hourly ecophysiological responses of trees to environmental factors into forest management decisions operating over a plantation harvest cycle. Determination of the appropriate signals to pass between simulators is an ongoing research challenge. Nevertheless, some insights have been gained from initial signal-transfer modeling studies. We distinguish signal-transfer modeling from response-transfer modeling. In the latter, outputs from one scale do not enter simulation algorithms of the larger scale models, but are simply aggregated to the larger scale.

Some exploration of signal-transfer modeling has been undertaken in two applications that examined environmental change impacts on forests (Luxmoore et al., 1990, 1998). In these studies atmospheric CO_2 enrichment and ambient ozone effects on foliar physiology were simulated with an hourly time-step ecophysiological model to obtain annual stem growth responses (tree-ring signals). These diameter growth responses to changes in air quality were incorporated into the algorithm of an annual time-step simulator of forest growth. The enhanced productivity of a deciduous forest simulated with CO_2 enrichment declined with time, whereas, ambient ozone exposure caused a small decline in simulated timber yield of a loblolly pine (*Pinus taeda*) plantation. In both cases short-term physiological responses induced the long-term result. An expanded development of signal-transfer modeling was initiated for regional assessment of forests in 13 states of the southeastern United States. This regional assessment method incorporates responses of several forest species to changes in precipitation, air temperature, tropospheric ozone, atmospheric CO_2, and N deposition (Luxmoore et al., 2000). Several aspects of this modeling development are examined in this report for their utility in sustainable management of southern pine forests. Comparisons of various management alternatives in the regional assessment modeling framework provide a means for evaluating practices that enhance or maintain forest productivity (site index) and ecosystem attributes over multiple rotations. This modeling method is adaptable to practical definitions of "sustainable forest management" for which measurable attributes such as stand productivity, soil organic matter or soil nitrogen may be determined. The signal-transfer method is adaptable to any ecosystem attribute represented in the signal-transfer suite of simulators.

In this report, we outline several aspects of information transfer between six models and describe two examples of signal-transfer identified by Luxmoore et al. (2000). We also discuss the inclusion of data variability with Monte Carlo simulation, application of response surface interpolation for signal-transfer and the use of spatial clustering as a means for identification of ecologically based forest management units. Finally, we address the incorporation of change in land quality (site index) into land-use modeling.

2. Signal-transfer modeling

Our most comprehensive development of signal-transfer modeling has been undertaken for regional assessment purposes (Luxmoore et al., 2000). In this development, the signal-transfer framework involves six models, empirical mensuration data summarized as forest growth types, and various spatial data in a GIS system (Fig. 1). The models in this scheme range from a detailed canopy irradiance model (MAESTRO) to a loblolly pine plantation management model (PTAEDA2). Management options such as forest fertilization, planting density, vegetation (weed) control and thinning may be addressed with this hierarchy of models; these management options are relevant to

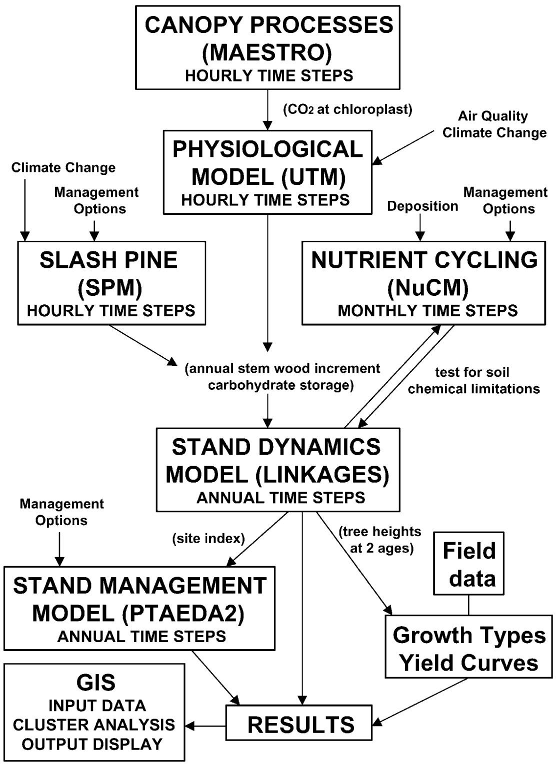

Fig. 1. Signal-transfer modeling framework: ecophysiological model (SPM, UTM) responses to air quality and climate change are transferred as annual stem wood increments to the scale of stand dynamics (LINKAGES), which translates to site index signals used in plantation management simulation (PTAEDA2) for loblolly pine applications. Outputs from LINKAGES combine with Growth Types to inferentially determine responses of several southern pine species for the selected scenario. Simulations with LINKAGES for slash pine may be combined with results for other pine species in a GIS. Soil chemical limitations to productivity are tested with the NuCM code. Various forest management options may be examined through the SPM, NuCM and PTAEDA2 models.

sustainable forest management. First we give brief comments on the component models in the hierarchy.

The MAESTRO model provides hourly calculations of light interception in a canopy, and the absorbed radiation values are used in photosynthesis subroutines incorporating leaf and atmospheric data to determine net primary production (Wang and Jarvis, 1990). A version of MAESTRO, specific for the physiology and canopy shape of loblolly pine (Baldwin et al., 1998), is used to calibrate a simple big-leaf photosynthesis algorithm in a whole plant simulator (UTM; Luxmoore, 1989). This model calibration is explained in a later section.

A loblolly pine version of the UTM (Luxmoore et al., 1998) and the slash pine model (SPM, Cropper and Gholz, 1993a,b) simulate ecophysiological processes (Fig. 1) with representation of above- and below-ground processes for two dominant pine species in the southeastern United States. The annual stem wood increments from SPM and UTM simulations are equivalent to tree-ring growth, and these "tree-ring" signals are transferred to either the slash pine or loblolly pine version of LINKAGES. The LINKAGES model of stand dynamics (Pastor and Post, 1986) simulates the establishment, growth and mortality of trees in a forest community or plantation using species-specific growth and longevity characteristics. The tree-ring signal enters the diameter-growth algorithm in LINKAGES as a scaler (0–1) normalized relative to a calibrated base case simulation. The average heights of dominant and codominant trees simulated in LINKAGES at a stand age of 25 years determine the site index signal used in plantation management simulations. Since N is the only nutrient simulated in LINKAGES, a soil nutrient cycling model, NuCM, is used to evaluate limitations to tree growth due to soil nutrients other than N (Liu et al., 1991a,b). Additional comments on the signal-transfer relationship between NuCM and LINKAGES are given in the later section. The significant contributions of the NuCM code to sustainable forest management include simulation of soil nutrient deficiency effects on growth and forest responses to fertilization as a management option.

The site index values simulated by LINKAGES for various scenarios are next transferred to the PTAEDA2 plantation management model (Burkhart et al., 1987) for determination of merchantable lumber production (Fig. 1). Management decisions involving planting density, vegetation control, fertilization and thinning may be examined with PTAEDA2 for loblolly pine plantations of the southeastern United States. Management practices that sustain ecosystem processes over several rotations under changing air quality and changing climate conditions may also be explored.

The determination of *growth types* for southern pine species by Zeide (1999) provides an opportunity for evaluating scenario impacts on southern pine species other than loblolly pine and slash pine. There are several southern pine species (white, *P. strobus*; shortleaf, *P. echinata*; Virginia, *P. virginiana*; longleaf, *P. palustris*; sand, *P. clausa*; pond, *P. serotina*) that grow in areas with loblolly pine. The responses of these other southern pines to selected scenarios of change may be estimated inferentially from simulations of loblolly pine. In this inferential method, scenario simulations of loblolly pine with LINKAGES provide average tree heights at two ages for determination of the height growth type by the two-point method of Zeide (1999). This simulated height growth type for a particular scenario is used to infer the expected growth of other southern pines from empirical relationships between loblolly pine growth and the growth of co-occurring southern pine species. This procedure extends the range of analysis to southern pine species that are not directly simulated; however, the method needs further development to determine its merits and limitations.

One advantage of the signal-transfer method is its ready use in specific applications where more is known of tree responses at a scale smaller than at the scale needed for management decisions. This was the case for the signal-transfer applications examining atmospheric CO_2 and tropospheric ozone effects on forests (see Section 1) in which foliar responses to air quality were integrated to the scale of stand productivity. Other ecophysiological simulators for loblolly pine, such as the TREGRO model of Constable and Retzlaff (1997), may be incorporated into the signal-transfer modeling hierarchy. Any of the models in Fig. 1 may be revised or replaced with suitable alternatives to incorporate new scientific information and developments.

Next, we address two examples of information transfer between modeling scales involving calibration of a big-leaf model of photosynthesis and soil nutrient limitations to productivity.

2.1. Calibration of a big-leaf model

The MAESTRO model provides a calibration constraint for a big-leaf model of net photosynthesis implemented in the UTM code. Net photosynthesis per unit leaf area is calculated in the UTM with a CO_2 gradient equation (Penman and Schofield, 1951) having the following form:

$$\text{Net photosynthesis} = A \times \frac{CO_{2A} - CO_{2C}}{R_m + R_s + R_b}, \quad (1)$$

where the A value converts CO_2 to an equivalent sucrose mass, CO_{2A} is the atmospheric CO_2 concentration, CO_{2C} the CO_2 concentration-at-the-chloroplast, R_m the mesophyll resistance, R_s the foliar stomatal resistance and R_b the boundary layer resistance.

The big-leaf photosynthesis model does not account for the self shading of leaves as leaf area increases with stand development. Calibration of the UTM photosynthesis calculation is undertaken by adjustment to the photosynthesis result obtained with detailed canopy light absorption relationships in MAESTRO. In this process a function is generated between the minimum value for CO_2-at-the-chloroplast (CO_{2C}) and leaf area index (LAI). This function causes photosynthesis per unit leaf area in the UTM to decrease with increase in LAI.

The MAESTRO model determines net photosynthesis for a three-dimensional canopy structure that accounts for differential light absorption by foliage (Wang and Jarvis, 1990). In this calibration, net photosynthesis values for optimal growing conditions were equated to the photosynthesis calculated in the UTM for the same conditions. Water stress and nitrogen limitations were excluded from the simulations of both models so that only shading effects were represented.

The CO_2-at-the-chloroplast variable in the UTM was adjusted to give the same daily net photosynthesis as simulated with MAESTRO at a particular LAI value. A mean minimum CO_{2C} was obtained for all of the hourly values simulated in a 30-day period without water and nutrient stress. The process was repeated for a range of LAI values to generate a calibration function.

This function was added to the UTM in the following form:

$$CO_{2C} = 98.98 + (15.72 \times LAI^{0.3787}). \quad (2)$$

The r^2 for this function is 0.999. An increase in LAI causes CO_{2C} to increase thus reducing the rate of net photosynthesis per unit leaf area in UTM calculations. The minimum value of CO_{2C} is 99 μl/l and this quantity rises to 128 and 137 μl/l at LAI values of 5 and 10, respectively.

Internal regulation of photosynthesis in UTM simulations operates by increasing CO_{2C} as leaf sucrose accumulates. Feedback regulation due to leaf sucrose accumulation is applied in addition to the specific minimum CO_{2C} selected for the LAI value in a particular simulation step. Leaf sucrose accumulation develops when environmental conditions, such as water stress or nitrogen limitation, reduce the tissue growth sinks for sucrose. Growth processes are more sensitive to these environmental stresses than is photosynthesis (Luxmoore, 1991). We note that Eq. (2), determined for UTM applications, may not be directly applicable to other big-leaf models.

The SPM model for slash pine has a layered canopy structure that directly accounts for shading effects.

2.2. Soil limitations to productivity

LINKAGES incorporates nitrogen cycling and provides stand growth responses appropriate for the soil organic matter and soil nitrogen status at a site. These capabilities have been utilized in simulation of loblolly pine growth responses to application of biosolids (Luxmoore et al., 1999). However, other soil nutrient limitations occur through the southeastern United States. The use of the NuCM code provides a means for simulation of soil nutrient limitation effects on pine growth due to P, K, Ca, Mg or S deficiency.

A two-step process is used. First LINKAGES determines tree growth as a function of stand age for a site and an environmental scenario of interest. The LINKAGES simulations of biomass as a function of time are next provided to NuCM. These values represent the maximum stand growth for the climate, water and nitrogen status of a site. Simulation with NuCM determines if this level of productivity can be sustained when P, K, Ca, Mg and S are included in the simulation of soil chemical processes.

NuCM determines an annual growth limitation factor that is applied to the annual productivity values from LINKAGES. Factor values less than unity result when nutrient limitations, such as phosphorus and potassium, develop. Soil variability is a significant reality at forest sites. We use Monte Carlo simulation methods to incorporate variability effects in all models of the signal-transfer hierarchy, including LINKAGES and NuCM.

3. Monte Carlo simulation

Essentially all aspects of biological and environmental processes involve variability. Monte Carlo simulation incorporates this variation in evaluations of alternative scenarios with the advantage that scenario results may be statistically compared. We use Latin hypercube sampling, an efficient Monte Carlo method (McKay et al., 1979) that requires relatively few simulations (e.g., 50–100) to incorporate the probability distributions of input variables. One concern with the propagation of variability from smaller to larger scales is the possibility of error multiplication through the hierarchy. We examine the consequence of variance transfer in Section 3.1 with results from a completed study conducted with three models and two signal-transfer stages.

3.1. Variance propagation

The signal-transfer modeling of ambient ozone effects on loblolly pine production (Luxmoore et al., 1998) involved information transfer between three models representing physiological processes (UTM), stand dynamics (FORET, a simpler version than LINKAGES) and plantation management (PTAEDA2). The coefficient of variation of simulated variables from these three models (Table 1) shows a consistent magnitude in the range of 1.5–3.8%. There is no evidence for expanding or compounding variance in this signal-transfer application. The signals introduced from a lower scale are incorporated into the modeling structure of the upper scale processes which constrain the expression of variance introduced from a lower scale. For example, variance in the stem increment multiplier (from the UTM) is applied to the biomass vs diameter function in FORET (same as in LINKAGES),

Table 1
Mean, standard deviation and coefficient of variation of variables from signal-transfer modeling with three simulators (UTM, FORET, PTAEDA2) for a scenario of ambient ozone exposure in a loblolly pine plantation (from Luxmoore et al., 1998)

	Mean	Standard deviation	Coefficient of variation (%)
UTM (ecophysiology, hourly simulation)			
Annual stem wood increment ratio[a]	0.946	0.035	3.7
FORET (stand dynamics, monthly simulation)			
Site index[b] at 25 years (m)	19.0	0.35	1.5
PTAEDA2 (forest productivity, annual simulation), 35 years harvest results			
Total basal area (m^2/ha)	23	0.6	2.6
Stem volume (m^3/ha)	250	6.7	2.7
Cordwood yield (cord/ha)	93	2.5	2.7
Lumber yield (board feet)	9910	380	3.8

[a] Variable transferred from UTM to FORET.
[b] Variable transferred from FORET to PTAEDA2.

which has decreasing diameter increments as tree size increases. This gives a damping influence on any signal coming from a lower scale model. Similarly, the variance in site index determined in FORET is constrained by the empirical relationships between loblolly plantation productivity and site index that are part of the structure of the PTAEDA2 model. The LINKAGES model, used in subsequent signal-transfer modeling, is derived from FORET by inclusion of algorithms for soil–plant nitrogen dynamics.

4. Other aspects

4.1. Response surface interpolation

Berry and Minser (1999) devised a method to record the responses of repeated simulation results for various combinations of environmental driving variables in hypervolume response surfaces. Response surfaces provide an archive of simulation results that define the output signals in relation to the driving variables at a particular scale. A hypothetical example is shown for two factors, atmospheric CO_2 and precipitation (Fig. 2). Relative stem growth responses for these two environmental variables is characterized with relatively few simulations shown by "×" in Fig. 2. Nonlinear interpolation of the relatively sparse population of simulations is used to characterize the whole surface across all variables. This approach is suitable where simulation results change smoothly with change in driving variables. The benefit of reduced computation time needed to characterize a response surface gains appreciably as the number of variable levels declines. For example, the number of simulations required for a factorial combination of five variables at three levels (3^5) is 781 simulations less than for four levels (4^5).

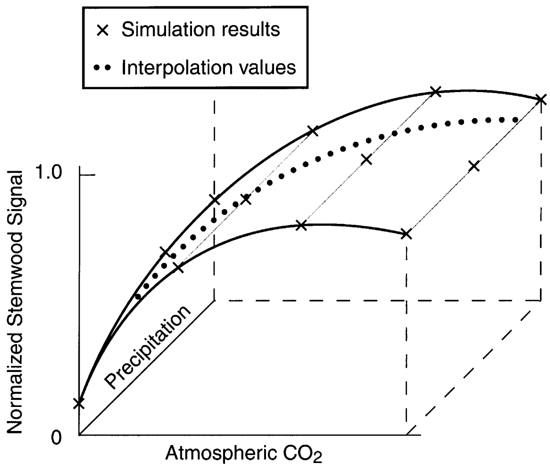

Fig. 2. A hypothetical response surface showing normalized stem wood growth responses to atmospheric CO_2 and precipitation variables. This smooth response surface is characterized by relatively few simulations (shown by ×). Transient scenarios use small increment changes in the stemwood response obtained in trajectories across the surface for sequential changes in atmospheric CO_2 and precipitation (shown by •). This procedure eliminates simulation with small scale models once the response surface has been determined.

Hypervolume response surfaces for five environmental variables are advocated in the regional assessment modeling of Luxmoore et al. (2000).

Following response surface characterization for selected scenarios, interpolation is used to obtain signal values appropriate for additional scenarios. Interpolation has the advantage of eliminating the need for repeated simulation with ecophysiological models (UTM, SPM, Fig. 1) in scenario applications. Berry and Minser (1999) included a multivariable interpolation technique for estimation of response surface values that are not specifically simulated. Their interpolation technique also allows transient scenarios to be readily undertaken by sequential interpolation at small increments, such as hypothetically shown by "•" in Fig. 2. Transient scenarios are relevant for addressing environmental change in relation to sustainable forest management.

4.2. Multivariate clustering

Hargrove and Luxmoore (1997, 1998) report a multivariate clustering method that determines areas in a region with predetermined ranges of variability of attributes within all clusters. Various climate, soil, vegetation and landscape data are used to statistically determine land groupings. This clustering method is a form of database stratification, and as such, provides a means for defining forest management units from ecologically relevant data. Higher numbers of clusters may be obtained by choosing clustering criteria that give lower variance of attributes within a cluster, i.e., smaller clusters become more uniform.

The application of clustering reported by Luxmoore et al. (2000) incorporated a constraint in which the clusters were contained within the boundaries of the major land resource area (MLRA) land classification system (USDA, 1981). In this procedure, the 78 MLRAs of the 13 southern and southeastern states provide an established land classification within which spatial clusters are statistically determined. This has the benefit of linking modeling results to other analyses that also use MLRAs, such as the land-use modeling of Hardie and Parks (1997). This method preserves landscape features such as river valleys showing that the identity of relatively fine scale and ecologically distinct land units can be maintained in regional-scale analyses.

4.3. Land quality (site index)

Hardie and Parks (1997) have shown that land quality is an important determinant of land-use and land-use change. Their modeling examines changes in the proportion of various categories of land-use in relation to timber price forecasts, price forecasts for agricultural commodities, and population growth. This land-use-share (LUS) modeling has been applied to five southeastern states (Virginia, North Carolina, South Carolina, Georgia, Florida) by incorporating county-based attributes and economic projections with four land-use categories (forest, farmland, irrigated farmland, urban/other). County-based estimates of land quality (productive capability) are derived from USDA land capability classes and the MLRA land classification.

Combining LUS modeling with signal-transfer modeling provides a means for combining economic factors into regional forest management planning. Thus, ecologically based environmental effects may be incorporated into economic forecasts of alternative forest land-use. Land quality indices are incorporated into LUS modeling with means and variances, and this provides a point of connection with signal-transfer modeling. Monte Carlo simulations of site index provided by signal-transfer modeling supplies the land quality index (mean, variance) needed for LUS modeling. The signal-transfer modeling results can be aggregated to a county basis from the proportional representation of cluster results contributing to a county. It is expected that significant change in land quality, predicted for a given environmental change scenario, could lead to changes in areas of various land-use categories, since the modeling of Hardie and Parks has shown the sensitivity of LUS to changes in land quality.

5. Discussion

Sustainable forest management has different meanings to different stakeholders, however, in all cases, management involves human interaction with the forest. Signal-transfer modeling can aid in determining suitable forms of human intervention that lead to sustainable products and services from forests. In the opinion of Powers and Morrison (1996) sustainable forestry centers on the wise management of soil. Tiarks and Haywood (1996) have noted that the productivity of short rotation pine plantations on infertile Coastal Plain soils of the southeastern United States can decline in the second rotation. Fertilizers and amendments such as lime are likely to be increasingly required for sustaining or enhancing forest productivity. The NuCM code has capability to address fertilizer management and liming requirements (Johnson et al., 1995). Issues of biodiversity of woody species in mixed forest communities may also be addressed with the forest succession capabilities of LINKAGES (Pastor and Post, 1986).

The selection of signal variables to pass from one simulator to another in the signal-transfer hierarchy involves consideration of model input and output variables and the algorithms that directly or indirectly relate to these variables. Our investigations with signal-transfer modeling have made pragmatic use of existing simulators and the selection of rather few signal variables. The benefits of signal-transfer modeling may be enhanced with additional transfers between modeling levels. Research on a fundamental basis for information transfer between model scales should add to the value and robustness of modeling by the signal-transfer method.

The determination of land units from statistical stratification of ecologically relevant data is a major advance for landscape analyses over analyses that employ arbitrary grid networks. For example, a 0.5° latitude $\times$ longitude grid has 672 cells across the 13 southeastern states. The average size of a grid cell is larger than the average size of the 1061 clusters obtained for the same region by our method (Luxmoore et al., 2000). Grid cells have essentially uniform size of 3368 km^2, whereas, clusters vary from 50 to 29,000 km^2 in area. All clusters are irregular in shape and contain similar variability of ecologically significant variables. Regular grids do not conform to the ecological realities of the landscape and cells contain widely differing variability of attributes. We advocate the use of MLRAs as a minimum framework for addressing land management issues, and recommend clustering within MLRAs as a flexible means for adjustment of cluster size as the need for more or less resolution is determined.

Several approaches have been undertaken in recent years to incorporate uncertainty analysis into forest growth models with methods that differ from the Latin hypercube sampling adopted in our signal-transfer modeling. Gertner et al. (1996) used Monte Carlo simulation to evaluate the influence of variation (error) of input variables (sensitivity analysis) of a forest growth model on the variance of output results. This output variance was partitioned in an error budget to the contributing input sources. Guan et al. (1997) assessed the accuracy of predictions of a forest growth model with Monte Carlo simulations that sampled assumed frequency distributions of model input variables. They also applied an alternative sampling approximation with an artificial neural network. Their work showed, as we have found, that relatively few variables have significant impacts on the uncertainty of simulation results. The neural network sampling approximation has merit where high dimensional and nonlinear interactions between variables are important contributors to variance propagation.

Green et al. (1999) conducted uncertainty analysis of a forest growth model with a Bayesian synthesis method. In their investigations, a Bayesian approach is used to obtain frequency distributions of input parameters for a stand growth model from uncertainty simulations of an ecophysiological carbon flux model. This follows the approach of Valentine et al. (1997). Their investigation has similarity with our use of uncertainty analysis in the signal-transfer hierarchy. However, our approach differs in that all input parameters and variables for all models are quantified prior to application by calibration with experimental data appropriate to the scale of each simulator (Luxmoore et al., 2000). We determine a modification (signal) to the value of a variable for a particular scenario relative to a calibrated base case and do not determine the absolute value of a transfer variable as undertaken by Valentine et al. (1997).

6. Conclusions

Signal-transfer modeling provides a means for gaining insight into possible large scale responses to impacts that have or can only be quantitatively investigated at a small scale. For example, stomatal responses to multiple environmental stressors may translate to a change in land quality (site index). Alternative management adaptations to changes in land quality may be statistically determined from Monte Carlo simulation results. The use of developed simulators at various scales in a signal-transfer hierarchy takes advantage of established quantitative relationships. New scientific advances may be incorporated into the modeling hierarchy at any scale by revision or replacement of the component models. Combining Monte Carlo simulation with a hierarchy of models in a signal-transfer structure provides the computational resources for statistically determining forest management practices that meet defined goals of sustainability.

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