Project Description

Results of Prior NSF Support

This project builds on several previous and ongoing NSF and EPA/NSF funded projects, including:

1. Human Settlements as Ecosystems: Metropolitan Baltimore from 1797-2100, NSF Long-Term Ecological Research (LTER) project, (R. Costanza and M. Wilson, co-PI's with Stewart Pickett and 12 others) 1997-2003 (with possible extensions). The aim of this project has been to study the spatial structure and temporal changes of socio-economic, ecological, and physical factors in the urban Baltimore area (http://baltimore.umbc.edu/lter/). The project has supported a broad range of ecological and socio-economic data collection activities, and the development of a multiscale suite of integrated dynamic simulation models at the site and watershed scales (Pickett et al. 2001).
2. Value of the World's Ecosystem Services and Natural Capital: Toward a Dynamic, Integrated Approach. Working Group supported by the National Center for Ecological Analysis and Synthesis, a Center funded by NSF, the University of California, and the Santa Barbara campus. This project provided a broad synthesis of theoretical and practical information on ecosystem services and their valuation (Costanza and Farber 2002). In particular, it supported the initial development of the The General Unified Meta-model of the BiOsphere (GUMBO – Boumans et al. 2002)
3. An Open Spatial Modeling Environment, NSF (subcontract with the NCSA, University of Illinois) (T. Maxwell and R. Costanza, PIs) 1998-2003 (with possible extensions). The aim of this project has been to develop the Spatial Modeling Environment (SME), a tool for modular, collaborative modeling and distributed computing (Maxwell and Costanza 1994, 1997; Maxwell 1999). The SME plays a key role in our suite of modeling activities.
4. Integrated Ecological Economic Modeling and Valuation of Watersheds, EPA/NSF Water and Watersheds program, (R. Costanza, PI) 1995-1999 (http://www.uvm.edu/giee/PLM). This project supported the initial development of the Patuxent Landscape Model (PLM) (Voinov et al. 1999; Costanza et al. 2002)
5. Whole Watershed Health And Restoration: Applying The Patuxent And Gwynns Falls Landscape Models To Designing A Sustainable Balance Between Humans And The Rest Of Nature, EPA/NSF Water and Watersheds program, (R. Costanza, PI, with R. Boumans, T. Maxwell, F. Villa, & A. Voinov) 1999-2003 (http://www.uvm.edu/giee/PLM). This project continued development and application of the PLM and GFLM. It has involved broad stakeholder participation in refining the models, designing scenarios and interpreting results (Costanza et al. 2002)
6. Regional Sustainability: Bridging Resource Conservation and Economic Development, NSF and its German counterpart (Deutscher Akademischer Austauschdienst), J. Erickson, co-PI, 2001-2002. To facilitate a research exchange between Rensselaer Polytechnic Institute, the University of Vermont, and the UFZ Centre for Environmental Research (Leipzing, Germany) on integrated watershed modeling and applications. The project has resulted in a book in progress (with Elsevier Science) on new developments in and new approaches to watershed management grounded in principles of ecological economics.
7. A web-accessible knowledge base for the integrated analysis and valuation of ecosystem services, NSF, (R. Costanza and F. Villa, Co-PIs) 2001-2004. This project supports extension of the ecosystem services data base initially begun in Costanza et al. (1997) and linkages to statistical and simulation models at multiple scales. In particular, it has supported the development of a comprehensive "knowledge base" on ecosystem functions and services (Villa et al. 2002) and the initial development of the The General Unified Meta-model of the BiOsphere (GUMBO – Boumans et al. 2002)

Further discussion of the results of these projects is integrated into the project description.

Background

This section provides a brief overview of scaling theory as it relates to this project, and sets the stage for the questions about scaling and dynamic behavior in the next section

Scaling

Systems exhibiting biocomplexity are characterized by non-linearities, autocatalysis, complex, time-delayed feedback loops, emergent phenomena, and chaotic behavior (Kauffman, 1993; Patten and Jorgensen 1995). This means that the whole is significantly different from the simple sum of the parts. This, in turn, makes scaling (the transfer of understanding across spatial, temporal, and complexity scales) not only a difficult problem, but probably the core problem in understanding biocomplexity (Ehleringer and Field 1993; O'Neill et al. 1989). The term "scale" in this context refers to both the resolution (spatial grain size, time step, or degree of complexity of the model) and extent (in time, space, and number of components modeled) of the analysis. The process of "scaling" refers to the application of information or models developed at one scale to problems at other scales. The scale-dependence of predictions is increasingly being recognized in a broad range of ecological studies, including: landscape ecology (Meentemeyer and Box 1987), physiological ecology (Jarvis and McNaughton 1986), population interactions (Addicott et al. 1987), paleoecology (Delcourt et al. 1983), freshwater ecology (Carpenter and Kitchell 1993), estuarine ecology (Livingston 1987), meteorology and climatology (Steyn et al. 1981) and global change (Rosswall et al. 1988). However, 'scaling rules' applicable to biocomplex systems have not yet been adequately developed, and limits to extrapolation have been difficult to identify (Turner et al. 1989). In many of these disciplines primary information and measurements are generally collected at relatively small scales (i.e. small plots in ecology, individuals or single firms in economics, census blocks in demographics and sociology) and that information is then often used to build models and make inferences at radically different scales (i.e. regional, national, or global). The process of scaling is directly tied to the problem of aggregation, which in complex, non-linear, discontinuous systems (like natural and human systems) is far from a trivial problem.

Aggregation

Aggregation error is inevitable as attempts are made to represent n-dimensional systems with less than n state variables, much like the statistical difficulties associated with sampling a variable population (Bartel et. al. 1988; Gardner et. al., 1982; Ijiri 1971). Cale et al. (1983) argued that in the absence of linearity and constant proportionality between variables—both of which are rare in ecological and economic systems—aggregation error is inevitable. Rastetter et al. (1992) give a detailed example of scaling a relationship for individual leaf photosynthesis as a function of radiation and leaf efficiency to estimate the productivity of the entire forest canopy. Because of non-linear variability in the way individual leaves process light energy, one cannot simply use the fine-scale relationship between photosynthesis and radiation and efficiency along with the mean values for the entire forest to represent total forest productivity without introducing significant aggregation error. Therefore, strategies to better understand aggregation error are necessary.

Rastetter et al. (1992) describe and compare four basic methods for scaling that are applicable to complex systems:

1) **partial transformations** of the fine-scale relationships to coarse scale using a statistical expectations operator;
2) **moment expansions** as an approximation to method 1, above;
3) **partitioning** or subdividing the system into smaller, more homogeneous parts (see the resolution discussion further on); and
4) **calibration** of the fine-scale relationships to coarse scale data.

They go on to suggest a combination of these four methods as the most effective overall method of scaling in complex systems (Rastetter et al. 1992).

Hierarchy

Hierarchy theory provides an essential conceptual base for building coherent models of complex systems at multiple scales (Allen and Starr 1982; O'Neill et al. 1986; Salthe 1985;

Gibson et al. 2000). Hierarchy is an organizational principle which yields models of nature that are partitioned into nested levels that share similar time and space scales. In a constitutive hierarchy, an entity at any level is part of an entity at a higher level and contains entities at a lower level. In an exclusive hierarchy, there is no containment relation between entities, and levels are distinguished by other criteria, e.g. trophic levels. Entities are to a certain extent insulated from entities at other levels in the sense that as a rule they do not directly interact; rather they provide mutual constraints. For example, individual organisms see the ecosystem they inhabit as a slowly changing set of external (environmental) constraints and the complex dynamics of component cells as a set of internal (behavioral) constraints.

From the scaling perspective, hierarchy theory is a tool for partitioning complex systems in order to minimize aggregation error (Thiel 1967; Hirata and Ulanowicz 1985). The most important aspect of hierarchy theory is that ecological systems' behavior is limited by both the potential behavior of its components (biotic potential) and environmental constraints imposed by higher levels (O'Neill et al. 1989). The flock of birds that can fly only as fast as its slowest member, or a forested landscape that cannot fix atmospheric nitrogen if specific bacteria are not present are examples of biotic potential limitation. Animal populations limited by available food supply and plant communities limited by nutrient remineralization are examples of limits imposed by environmental constraints. O'Neill et al. (1989) use hierarchy theory to define a "constraint envelope" based upon the physical, chemical and biological conditions within which a system must operate. They argue that hierarchy theory and the resulting "constraint envelope" enhance predictive power. Although they may not be able to predict exactly what place the system occupies within the constraint envelope, they can state with confidence that a system will be operating within its constraint envelope.

Viewing biocomplexity through the lens of hierarchy theory should serve to illuminate the general principles of life systems that occur at each level of the hierarchy. While every level will necessarily have unique characteristics, it is possible to define forms and processes that are isomorphic across levels (as are many laws of nature). Troncale (1985) has explored some of these isomorphisms in the context of general system theory. In the context of scaling theory we can seek isomorphisms that assist in the vertical integration of scales. These questions feed into the larger question of scaling, and how to further develop the four basic methods of scaling mentioned above for application to complex systems.

Resolution and Predictability

The significant effects of nonlinearities raises some interesting questions about the influence of resolution (including spatial, temporal, and component) on the performance of models, and in particular their predictability. Costanza and Maxwell (1994) analyzed the relationship between resolution and predictability and found that while increasing resolution provides more descriptive information about the patterns in data, it also increases the difficulty of accurately modeling those patterns. There may be limits to the predictability of natural phenomenon at particular resolutions, and "fractal like" rules that determine how both "data" and "model" predictability change with resolution.

Some limited testing of these ideas was done by resampling land use map data sets at several different spatial resolutions and measuring predictability at each. Colwell (1974) used categorical data to define predictability as the reduction in uncertainty (scaled on a 0-1 range) about one variable given knowledge of others. One can define spatial auto-predictability (P_a) as the reduction in uncertainty about the state of a pixel in a scene, given knowledge of the state of adjacent pixels in that scene, and spatial cross-predictability (P_c) as the reduction in uncertainty about the state of a pixel in a scene, given knowledge of the state of corresponding pixels in other scenes. P_a is a measure of the internal pattern in the data, while P_c is a measure of the ability of some other (i.e. modeled) pattern to represent that pattern.

A strong linear relationship was found between the log of P_a and the log of resolution (measured as the number of pixels per square kilometer). This fractal-like characteristic of "self-similarity" with decreasing resolution implies that predictability, like the length of a coastline, may be best described using a unitless dimension that summarizes how it changes with resolution. One can define a "fractal predictability dimension" (DP) in a manner analogous to the normal fractal dimension (Mandelbrot 1977, 1983). The resulting DP allows convenient scaling of predictability measurements taken at one resolution to others.

Cross-predictability (P_c) can be used for pattern matching and testing the fit between scenes. In this sense it relates to the predictability of models versus the internal predictability in the data revealed by P_a. While P_a generally increases with increasing resolution (because more information is being included), P_c generally falls or remains stable (because it is easier to model aggregate results than fine grain ones). Thus we can define an optimal resolution for a particular modeling problem that balances the benefit in terms of increasing data predictability (P_a) as one increases resolution, with the cost of decreasing model predictability (P_c).

Some questions we want to investigate are whether these results hold for complete landscape models (like the PLM) and whether they are generalizable to all forms of resolution (spatial, temporal, and complexity), as described in more detail below.

Questions

The research consists of three parts: (1) developing the conceptual schema and mathematical formulations for the models (with broad scientist and stakeholder involvement as described in the Approach section); (2) testing the models against real-world data (described below in the Approach section); and (3) using the tested and calibrated models to address several important questions about complex systems as described in this section. The questions are grouped into two categories: (1) questions about space, time, and complexity scaling; and (2) questions about the dynamic behavior of complex coupled natural and human systems at multiple scales.

Scaling in Space, Time and Complexity

1. How does the predictability of patterns in data and model results vary with resolution (in space, time and complexity)

This is a specific question about the way a particular measure of information changes with resolution. It is based on some preliminary results reported in Costanza and Maxwell (1994), as described above. The question has yet to be investigated with real models, as we will do in this project. If we discover that (as in the preliminary results) a “fractal” (or some other) relationship between resolution and predictability holds up, it could be very useful in understanding the effects of changing resolution and designing models with "optimal" (cost/effective) resolution.

2. What factors control the divergence between models or measurements at one scale and another? We will initially look at three categories of interrelated factors:

(A) *parameter variability* (i.e. between spatial cells or between models of different complexity). For example, if one is spatially aggregating an area which consists of very different habitat types to a single habitat type, the divergence would be greater than if one were aggregating an area of very similar habitat types. The PLM and GUMBO characterize habitats (or biomes) by their parameter values in a generalized dynamic model (Fitz et al. 1996), and this measure of variability may be useful in scaling.

(B) *existence of critical thresholds* (i.e. non-linear effects). For example, if one is aggregating two components, one of which goes through a critical threshold, the behavior of the aggregate (average) component will diverge significantly from the behavior of the sum of the two components evaluated independently. The same applies for spatial and temporal resolution: if a threshold in the finer scale is overlooked when switching to a coarser grid, the models and measurements can be dramatically misleading (anoxia at night may result in fish-kills even while the daily average oxygen content is well above critical levels). The PLM and GUMBO incorporate nonlinear dynamics and can thus address this issue directly.

(C) *degree of independence* (i.e. between spatial cells or between components in a system). For example, if spatial cells are relatively isolated or independent, then aggregating them will cause more divergence than if they are highly interdependent, where the behavior of one is correlated with the behavior of the other. The PLM and GUMBO incorporate interdependence between spatial cells and model components explicitly and can address this issue directly.

3. Can aggregation of models and measurements in one dimension (spatial, temporal or complexity) be compensated with disaggregation in another?

To a certain extent the detail that is lost when aggregating over space can be compensated by added model complexity. For example, incorporating the spatial variance in a landscape (measured at a high spatial resolution) as an explicit variable in a model at lower spatial resolution may help to compensate for the divergence caused by loss in spatial parameter variability. In a similar way, adding more complexity to the algorithms involved can potentially compensate for the losses in accuracy due to decreased temporal resolution. We intend to study the possible trade-offs in aggregating along these three dimensions in order to identify the dimensions that are most beneficial for aggregation in terms of costs and effort.

Understanding the role of scale is essential to answering the following questions about system dynamics.

Dynamics of Coupled Natural and Human Systems

1. How is the provision of ecosystem services of value to humans affected by the resilience and sustainability of ecological life-support systems?

Ecosystem services represent an important and valuable set of endpoints for ecosystem management (Lubchenco et al. 1991, Millennium Ecosystem Assessment - http://www.millenniumassessment.org/en/). To address important questions about ecosystem services, we have developed initial versions of dynamic models at regional and global scales which explicitly link natural and human systems via ecosystem services (Costanza et al. 2002, Boumans et al. 2002). After significant further development, outreach, and testing, we will use these models to assess the relationship of ecosystem services provision over time to the resilience and sustainability of the supporting natural system. The models will also be used for scenario analysis (in consultation with stakeholders) with effects on ecosystem services, natural capital, and human welfare as the major integrating components for evaluating alternative scenarios.

2. How is the sustainability of a complex coupled natural and human system related to its vigor (productivity), organization, and resilience?

Based on a survey of concepts in many fields, Costanza (1992) developed the following three general categories of performance that are usually associated with "well-functioning" in any complex living system at any scale:

1. The **vigor** of a system is a measure of its activity, metabolism or primary productivity. Examples include metabolic rate in organisms, gross and net primary productivity in ecological systems, and gross national product in economic systems.
2. The **organization** of a system refers to the number and diversity of interactions between the components of the system. Measures of organization are affected by the diversity of species, and also by the number of pathways and patterns of material and information exchange between the components.
3. The **resilience** of a system refers to its ability to maintain its structure and pattern of behavior in the presence of stress (Holling 1986). A healthy system is one that possesses adequate resilience to survive various small scale perturbations. The concept of system resilience has two main components: (1) the length of time it takes a system to recover from stress (Pimm 1984); and (2) the magnitude of stress from which the system can recover, or the system's specific thresholds for absorbing various stresses (Holling 1986).

The suite of models described in this proposal can assess the vigor, organization, resilience , and sustainability of the modeled systems at several scales from individual sites to global. If vigor, organization, and/or resilience turn out to be good predictors of sustainability, then a whole new suite of indicators applicable at several scales could be developed to help us to better understand and achieve the important goal of sustainability.

3. How can we better understand and display the full range of uncertainty about models of coupled natural and human systems?

Analysis and display of model uncertainty is often limited to parameter uncertainty. Adequate methods of parameter sensitivity analysis exist (discussed briefly below) and we will fully explore the uncertainty in model results due to parameter uncertainty. But other sources of uncertainty can be equally, if not more, important. In this project we will investigate a broader range of sources of model uncertainty, including (in addition to parameter uncertainty) the uncertainty due to model structure and resolution, and to data quality. Model structure uncertainty will be analyzed by maintaining a suite of intercomparable models that employ a range of assumptions about model structure. The global climate modeling community has successfully used this approach by doing systematic model intercomparison studies (http://gaim.unh.edu/). The scaling questions discussed above (and the scaling experiments discussed below) are also a part of this analysis, since they allow a systematic variation of model resolution and complexity. Uncertainty due to data quality will be addressed by using a system of data grading and an arithmetic for combining grades that is part of the Ecosystem Services Database we are developing (Villa et al. 2002). We have adapted the system developed by Funtowicz and Ravitz for this purpose (Funtowicz and Ravitz 1987, Costanza et al. 1992). This database will feed not only raw data but also the data "grades" into the models.

Approach

This project will use as a starting point a suite of complex dynamic simulation models developed by our group over the last several years (Costanza et al. 1990, 1993, 2002, Voinov et al. 1999, Boumans et al. 2002). The project will allow the continued development, outreach, integration, calibration and testing of this suite of models. The models explicitly address the linked dynamics of natural, human, built and social capital, and the role of ecosystem functions and services. They allow the integrateion of site-specific information with regional and global surveys, GIS, and remote sensing data. The models are individual and process-based, spatially explicit, dynamic, non-linear simulations (including carbon, water, nitrogen, phosphorous, plants, consumers (including humans) and a range of ecosystem services) under various climate, economic, and policy scenarios. They can exhibit "catastrophic," irreversible changes of system structure and function at specific sites and can, therefore, be used to test hypotheses about system resilience and sustainability across a range of scales.

We will investigate the questions listed above by conducting a series of experiments using this suite of models at a range of spatial and temporal scales from individual sites to watersheds to global, as described below. These models will first be further calibrated and tested with extensive spatial and time series databases which will be incorporated into a comprehensive web-accessible "knowledge base" we are developing as part of a related NSF-funded project (Villa et al. 2002).

The databases include:

1. spatial remote sensing data (i.e. NDVI) as well as spatial coverages that are derived from both remote (satellite, air photo) and groundtruth operations (DEM - digital elevation models, land use and land cover maps, etc.)
2. time series data, measured at specific sites (meteorological data, stream gauging series, tree core analysis, etc.); economic data, census data, Maryland Property View (information on land values, etc.), BES-LTER surveys and interviews, the World Values Survey (World Values Study Group, 1997), etc.)
3. rate coefficients, measured in intensive studies both in situ and in vitro (i.e. growth and uptake rates, half saturation coefficients, mineralization rates, etc.). We will supplement extensive literature reviews with some original field and survey-based research to develop these coefficients.

Our suite of models links the three tiers of currently available monitoring data. The models are therefore instrumental in putting all the available data within a common framework allowing cross-scale comparisons and analysis.

The rest of this section introduces the multi-scale, modular modeling environment and suite of models, discusses tools for model calibration and testing, and briefly describes model-based experiments to address the project's questions. Due to the number and complexity of the models involved and page limits, we cannot possibly describe the full suite of models in any depth. We attempt below to give enough information to allow an overview of the approach.

Modeling Environment and Models

Spatially explicit, dynamic simulation models allow one to link knowledge about the function and dynamics of coupled human and natural systems at the site level (where most information is collected) to the behavior of the entire region, landscape or globe (where the management questions are). They can also be used to generate future scenarios of predicted environmental change as a result of various management policies. Our results thus far (Costanza et al. 1990; Fitz et al. 1993; Bockstael et al. 1995; Voinov et al. 1999; Costanza et al. 2002) indicate the feasibility and utility of this approach. One continuing problem, however, is the expense (in manpower and time) to adequately implement this approach. This leads to the need to aggregate and simplify. To do this intelligently (rather than arbitrarily) one needs to fully understand the information losses that accompany various aggregation and simplification schemes. This will be discussed in further detail in the section on scaling below.

Computational Aspects of Multi-Scale Modeling

To address the conceptual and computational complexity barriers to landscape modeling, our team has developed an integrated environment for high performance, modular, multi-scale spatial modeling called the Spatial Modeling Environment (SME: Maxwell and Costanza, 1994; Maxwell and Costanza 1997). The SME links icon-based modeling environments with distributed computing resources, allowing scientists to develop models graphically, and to transparently access state-of-the-art computing facilities. The SME supports archiving of reusable modules in our Simulation Module Markup Language (SMML: Maxwell 1999), allowing modelers to exchange model components and to build new models from an existing library of components. The SME Java Portal provides the user with a single familiar environment in which to build, configure, execute, and visualize simulations running on a wide range of parallel or serial computers (more details are available at: http://www.uvm.edu/giee/SME3/). We have used this modeling environment to develop the suite of models, described here.

Integrated Multi-scale Simulation Models

We have been developing a nested suite of individual and process-based models of complex coupled human and natural systems ranging from individual sites (Individual Based Models (IBMs) of forests, agent-based models of urban neighborhoods, and the process-based General Ecosystem Model (GEM) and General Human System Model (GHSM), to mixed use landscapes (the Patuxent and Gwynns Falls Landscape Models – PLM and GFLM) to Global (The General Unified Meta-model of the BiOsphere – GUMBO). These are briefly described below (more details are available at: http://www.uvm.edu/giee/PLM/, and http://www.uvm.edu/giee/GUMBO/). In addition we will use versions of other models at various scales for cross-calibration, intercomparison, and scaling, including: the HSPF hydrologic model at the watershed scale, and Earth system Models of Intermediate Complexity (EMIC's – Claussen et al. 2002) at the global scale.

Individual Based Models (IBMs) of forests and urban neighborhoods

Individual-based models (IBMs) are valuable for understanding how species interactions influence biodiversity, community dynamics, ecosystem processes, and generation of ecosystem services (DeAngelis et al. 1994: Huston et al. 1988). Forest IBMs have a long history of application in assessing effects of interspecific competition (Botkin et al. 1972; Shugart 1984; Vance 1996; Bugman 2001), various exogenous disturbances (Bugman et al. 2001; Doyle 1981; Seagle and Liang 2001; Pastor and Post 1988; Shugart and West 1977), and forest succession (Pacala et al. 1996; Pastor and Post 1986, Erickson et. al. 1999) on emergent ecosystem properties such as biomass production and nutrient storage. Previous studies have used forest IBMs to estimate transition parameters for Markov models (Acevado et al. 1995), thus aggregating the cumulative interactions of individual trees based on functional roles (Acevado et al. 1996) or simulated stand characteristics and cover type (Acevado et al. 2001). These approaches have not, however, related aggregated forest characteristics to nutrient dynamics or used forest IBMs for generation of rate parameters in landscape-scale process models. Thus we will focus on applying forest IBMs to (1) understand effects of aggregation strategies within the

IBM on emergent ecosystem services, and (2) parameterize the forest growth and nutrient cycling algorithms in landscape process models (see the "Complexity Scaling Experiments" section for further details).

We will develop an individual-based modeling approach referring to the JABOWA/FORET class of models (Botkin et al. 1972, Shugart 1984). The model will be further calibrated for the Gwynns Falls watershed, and N cycling algorithms from the LINKAGES model (Pastor and Post 1985, 1986, 1988) will be incorporated to simulate nutrient dynamics. These algorithms are based on species-specific decomposition rates of tree tissue (derived through lignin:N ratios), thus allowing estimation of species impacts on nutrient dynamics. This feedback between decomposition processes and forest stand growth will allow us to examine how aggregation within an IBM affects ecosystem N cycling and forest parameter estimation for landscape models (Fitz et al. 1996; Costanza et al., 2002).

Agent-based models in the social sciences (Axelrod 1997; Arthur et al. 1997; Luna and Stefansson 2000; Gimblett 2001) can be seen as a parallel development with IBMs in ecology, sharing many of the same concepts and techniques, but with only limited dialogue between the researchers involved (Costanza et al. 1993). As part of this project, we will develop an agent-based simulation model of an urban neighborhood, linked with the other work in the BES project. This model will be used in a manner analgous to the forest IBM described above. Individual human agents in this model make decisions based on a set of rules and imperfect information they have about their neighbors and the larger biophysical and social context. We think that the most appropriate use of agent-based models of human behavior is at this small, neighborhood scale. We can then use this model to better understand individual behavior and to help us scale up that understanding using the process-based and landscape models and scaling experiments described below.

<u>The General Ecosystem Model (GEM)</u>

The GEM (Fitz et al. 1996) and its extensions (Voinov et al. 1999, Boumans et al. 2001, Costanza et al. 2002) is a process-based model that includes modules for hydrology, nutrient movement and cycling, terrestrial and estuarine primary productivity, animal consumer dynamics, and human system dynamics. It is intended to apply at the site, patch, or "unit cell" level to a broad range of ecosystems, including forests, estuaries, wetlands, grasslands, and agroecosystems. The GEM is currently highly developed and well tested (Boumans et al. 2001) and is used as the unit model in the landscape models discussed below.

<u>The General Human System Model (GHSM)</u>

The GHSM is intended to run in parallel with the GEM to model urban and suburban sytems at the patch or neighboorhood scale. The spatial and temporal resoloution of GHSM need not be the same as GEM, however. While GEM models the "natural capital" stocks and the flows in and out of them, the GHSM includes three major types of "human made capital" stocks and all their related inflows and outflows.

1. *Built capital*, including the human-made physical infrastructure and material resources of the economy and economic production. All built capital requires natural capital inputs. At the unit level, these natural capital inputs may not be local, but physical infrastructure must still displace natural capital. Built capital must also inevitably return to the natural system as waste, with subsequent impacts on the production of natural capital. Construction expenditures and the value of built infrastructure serve as proxy measures for built capital.
2. *Human capital*, including the human population and the accumulated education, training and experience of the individuals in a population, which is increased by the acquisition of new knowledge and capabilities. Human populations and years of education serve as proxies for human capital.
3. *Social capital*, including the quality and quantity of civic engagement and social connections within a society, which affects economic development, government effectiveness, and other measures of human welfare. Such connections can be the product of informal networks of mutual trust or more formal rules and norms (Putnam, 1995). Subjective measures of interpersonal trust and self-reports of community involvement provided by surveys and

interviews serve as proxy measures for social capital.

All four types of capital facilitate economic production and also contribute directly to human well-being (Costanza et al. 1997b).

The GHSM has been developed simultaneously at both the watershed scale as part of the Baltimore Ecosystem Study (BES) LTER project and at the global scale as part of the GUMBO model (both described in a little more detail below). The BES project is collecting extensive and unique data on natural, built, human, and social capital in Baltimore and the GHSM will be calibrated and tested using data collected as part of that project at the patch and watershed scales. As part of the GUMBO model, the GHSM has also been initially formulated, calibrated and tested (Boumans et al. 2002) and will continue to be developed and tested as part of the further development of GUMBO described later.

Landscape Models:

The Patuxent Landscape Model (PLM*)* (http://iee.umces.edu/PLM) effort is an outgrowth of a model first developed for Louisiana wetlands (Costanza et al., 1990) and later expanded and applied to the Florida Everglades (Fitz et al., 1993). The landscape is depicted as a grid of cells with a minimum cell size of 200m x 200m (or 30m x 30m for individual subwatersheds) to allow adequate depiction of the pattern of ecosystem processes and human settlement on the landscape. A unit model (some version of GEM) is embedded in each cell in the landscape, and all the unit models are run simultaneously. While the unit model simulates processes within a cell, horizontal fluxes link the cells together across the landscape to form the full landscape model. These spatial fluxes are driven by various processes. For example, cell-to-cell head differences of surface and ground water in saturated storage drive horizontal water fluxes. Water fluxes between cells carry dissolved and suspended materials and determine water quality in the landscape. The modular structure is important for flexible model adjustments and scaling experiments.

The PLM has been calibrated and tested for a variety of subwatersheds (spatial domains) and external conditions (scenarios in the temporal and spatial domains) (Voinov, et al. 1999, Costanza, et al., 2002). We used a modular, multiscale approach to calibrate and test the model. Certain modeled variables, or indices that aggregate model variables, were compared to available point time series data such as streamflow, nutrient concentration in the streams, and historical tree-ring data for the region. For example, modeled surface water flow was calibrated against the 13 USGS gauging stations in the area that have data concurrent with the climatic data series (1990-96). We have also compared some of the flow statistics to calibration results from the Hydrologic Simulation Program—Fortran (HSPF) (Donigian et al., 1984) that has been previously applied to the Patuxent watershed (AQUA TERRA, 1994). We attained a better fit to the hydrologic data with our model than with HSPF. HSPF is a more empirically based model that uses high temporal resolution input data (e.g. hourly rainfall data), but relatively low spatial resolution (e.g. aggregated subwatersheds). Much more of the behavior in HSPF is embedded in the parameters of the model than is the case in the PLM (which uses the pattern of land use to drive much of the behavior). Thus our approach seems to be especially useful to assess the effects of changes in the spatial pattern of land use (one of our key questions). PLM also goes far beyond hydrology, including also nutrients, vegetation dynamics, and agricultural and urban system dynamics.

The PLM has been used to analyze a range of scenarios that show the implications of alternative future policies in the watershed on the system. We analyzed 18 scenarios including: (1) land use in 1650, 1850, 1950, 1972, 1990 and 1997; (2) a “buildout” scenario based on fully developing all the land currently zoned for development; (3) four future development patterns based on a companion economic land use conversion model; (4) agricultural “best management practices” which lower fertilizer application; and (5) four “replacement” scenarios of land use change to analyze the relative contributions of agriculture and urban land uses; and (6) two “clustering” scenarios with significantly more and less clustered residential development than the current pattern. Results indicate the complex nature of the landscape response and the need for spatially explicit modeling (Costanza et al. 2002). The Gwynns Falls Landscape Model

(GFLM) is an application and extension of the PLM to a largely urban watershed in Baltimore as part of the BES project (http://www.ecostudies.org/bes/). As part of this project, we will be building the relevant database for the Baltimore watershed, further developing and testing the "human" components of the model (the GHSM described above), and integrating the natural (GEM) and human (GHSM) components of the model to run in a spatially explicit mode at the watershed scale.

The General Unified Meta-model of the BiOsphere (GUMBO)

A Global Unified Metamodel of the BiOsphere (GUMBO) was developed to simulate the integrated earth system and assess the dynamics and values of ecosystem services (Boumans et al. 2002 - http://www.uvm.edu/giee/GUMBO/.). It is a "metamodel" in that it represents a synthesis and a simplification of several existing dynamic global models in both the natural and social sciences at an intermediate level of complexity. The current version of the model contains 234 state variables, 930 variables total, and 1715 parameters. GUMBO is the first global model to include the dynamic feedbacks among human technology, economic production and welfare, and ecosystem goods and services within the dynamic earth system. GUMBO includes modules to simulate carbon, water, and nutrient fluxes through the *Atmosphere*, *Lithosphere*, *Hydrosphere*, and *Biosphere* of the global system. Social and economic dynamics are simulated within the *Anthroposphere*. GUMBO links these five spheres across eleven biomes, which together encompass the entire surface of the planet. The dynamics of eleven major ecosystem goods and services for each of the biomes are simulated and evaluated. Historical calibrations from 1900 to 2000 for 14 key variables for which quantitative time series data was available (8 land use change variables, atmospheric carbon, fossil fuel production, global average temperature, sea level, human population, and gross world product) produced an average R^2 of .922. A range of future scenarios representing different assumptions about future technological change, investment strategies and other factors have been simulated. The relative value of ecosystem services in terms of their contribution to supporting both conventional economic production and human well-being more broadly defined were estimated under each scenario, and preliminary conclusions drawn. The current version of the model can be downloaded and run on the average PC to allow users to explore for themselves the complex dynamics of the system and the full range of policy assumptions and scenarios.

As part of this proposal, we will significantly expand on the initial "proof of concept" work already comopleted on GUMBO. We will:

1. Greatly expand the range of international collaborators on the project by making GUMBO a core project of GAIM. In addition we will use our ongoing partnership with Jan Rotmans at the International Center for Integrative Studies (ICIS) at Maastricht University to facilitate ongoing international colaboration on the project.
2. Make GUMBO spatially explicit at the global scale. We will explore several possibilities for how to do this and at least a few of these possibilities will be implemented and compared as part of our analysis of model structure uncertainty. Two initial possibilities include: (1) implement the current GUMBO as a unit model in a manner parallel to the the use of GEM/GHSM as a unit model in the spatially explicit landscape models described above; (2) link parts of GUMBO (i.e. the Anthroposphere and the ecosytem service components) with existing intermediate complexity earth system models (EMICs - Claussen et. al. 2002). This approach will involve extended travel for project participants to visit sites where these models are under development.
3. Expand the range of data used for calibration and testing (see below), expecially for the spatially explicit implementations of GUMBO.
4. Perform a through uncertainty analysis on all versions of the model (see below), including parameter, model structure, and data quality uncertainty.
5. Expand the outreach aspects of the model by soliciting broad input on the model's formulation and testing (via GAIM and specific workshops on GUMBO) and by making the model and its results fully accessable over the web.

Testing and Calibration of Complex Models

We can distinguish between model *testing* or *evaluation* (assessing the degree and significance of fit of the model with data or with other models) and *calibration* (the adjustment of model parameters to improve the fit). Unlike simple statistical models, there are no universally accepted methods for testing or calibrating complex dynamic, non-linear simulation models (Berk et al. 2000). In fact, this is an active area of research and we hope that this project will contribute some new insights. We will follow the recommendations of Berk et al. (2000) and apply a range of visualization techniques and quantitative statistical tests informed by the specific context of the problem. The human brain is a powerful pattern processor, and if model output can be presented in appropriate formats, direct visual comparisons of models with data can yield significant insights about model performance. In addition, complex models must generally be tested against a broad range of data of varying types, quality, and coverage. For example, for some variables we may have only scattered field measurements, while for others we may have more complete time series data or even maps, while others may have no quantitative data at all, but only qualitative assessments. As discussed above, a system is therefore necessary for ranking or grading the relative quality of the data and the relative importance of the variables to be fit. We will also test our models over multiple resolutions (in time and space) in order to better understand the nature of the fit (Costanza 1989; Turner et al. 1989). We are also developing a multi-criteria based Model Performance Index (MPI: Villa, 1997; Villa et al., in review) that allows the user to weight the variables going into a quantitative overall model performance score.

The difficulty of calibrating complex models by manually adjusting parameters can be overwhelming, and, as Beaven (1993) points out, an optimal parameter set may not even exist. It is therefore more appropriate to recognize the uncertain nature of the process, to focus on finding "good" parameter sets, and to create a better way of defining what a “good” parameter set is in the first place.

In order to use the computer to optimize parameters, however, a quantitative overall score (like the MPI) is essential. To aid the calibration process we are developing a suite of optimizers exploiting the MPI scoring system (Boumans et al. 2001). The toolkit includes easy-to-use tools to explore a model's parameter space in a variety of ways, using the most efficient combinations of search techniques like genetic algorithms and hill climbing. The toolkit allows the quantification of a model's complexity and predictability, and can yield useful information about all aspects of a model's response to parameter change.

Scaling Experiments

Spatial Scaling Experiments

The scaling method of "partitioning" mentioned above is used in spatially explicit models to combine site-specific models and data into regional scale models. The PLM, GFLM and GUMBO use this approach. A key question has to do with the level or resolution of the spatial partitioning required to achieve adequate results. Should we subdivide the region into 2, 200, 20,000, or 2,000,000 spatial cells? Before we can answer this question, we need to understand in more detail the effects of different levels and methods of spatial aggregation on both the data and the model. Landscape and global models are the effective test beds for this kind of experimentation. For example, the full PLM model in its highest resolution form can contain over 60,000 spatial cells, each with a unit model of 21 state variables running with a daily time step. We plan to perform several aggregation experiments using a calibrated version of the model to develop this understanding by comparing the results of the full resolution PLM to various spatially, temporally, and complexity aggregated versions.

Temporal Scaling Experiments

Initial temporal scaling experiments will consist of running the hydrologic component at a range of different time steps, from 1 hour to 1 week or more, first holding the spatial and complexity resolution constant, and then modifying the latter in an attempt to compensate for the loss of the important details in the temporal resolution (checks for threshold effects, adjustments for mass conservation, etc.). We will search for aggregation algorithms that produce the best correspondence with the high temporal resolution model runs. Later experiments will expand to other model components.

Complexity Scaling Experiments

Complexity scaling experiments will be performed initially on the unit models (IBMs and GEM). Complexity scaling assumes model modifications along two lines: variations in the set of model state variables (structural aggregation) and variations in the links and formalizations of processes involved (functional aggregation).

Experimental manipulation of the forest IBM will include the two most common approaches to aggregation of tree species: (1) taxonomically; and (2) by functional role (Shugart 1984). Response variables for comparison among aggregation types will include: forest standing biomass, biomass N, forest litter biomass, and litter N. The differential effects of these aggregations will provide insight into the implications for carbon and N storage in models where complexity is simplified by different means. Because one ultimate goal of this part of the project is to develop parameters for the landscape models (PLM and GFLM) and the global model, these model experiments will help distinguish the effect of different approaches to aggregation on forest parameters. Such differences may prove crucial for how forest patches interact with lateral fluxes of nutrients in the landscape models.

Experimental manipulation of the GEM unit model will involve reducing its complexity from the current 21 state variables to 15, 10 and 5 state variables using various aggregation schemes. We will then compare the results of the low resolution models with the original high resolution models. All aggregation schemes lose detailed information but may gain understanding of general system performance. What we are after is finding what type of information is lost with each scheme and how aggregation might increase our knowledge about general system properties.

Cross Calibration Experiments

We will also perform several cross-calibration experiments between our process-based site models (GEM) and other, higher complexity resolution modeling formulations (IBMs), as a type of complexity scaling. Aggregation of IBM results and extension to simulate ecosystem health and services at larger spatial scales is also imperative. The GEM model will be used to understand this aggregation and extension. By analyzing aggregation effects within a forest IBM and also using this IBM to parameterize (cross calibrate) the forest component of GEM we will examine (1) the consequences of aggregation and concomitant loss of functional complexity for the relationship between ecosystem health and production of ecosystem services, (2) the effect of forest model complexity/resolution on production of local and landscape-scale ecosystem services, and (3) the interactive effects of spatial and temporal forest model aggregation.

Characterizing Dynamic Behavior

The questions about dynamic behavior in coupled natural and human systems can also be addressed with the suite of models we have described. The relationship between the provision of ecosystem services of value to humans and the sustainability of ecological life-support systems can be directly assessed in the models since they include ecosystem services d and sustainability can be assessed by observing the long term behavior of the sytem. Since our suite of models contains three distinct spatial scales (site, landscape, and global) and several possible time scales, we can also compare the sustainability of modeled systems with their time and space scales. One important distinction is whether the models are hierarchically nested and interconnected or run independently at their various scales. We suspect that only in the former case will the proposed relationship between scale and sustainability emerge. The models also contain variables (i.e. productivity) or indices that can be calculated from the models (i.e. organization and resilience) that can be used to predict the sustainability of various other components in the models. A predictive index of sustainability would be an enormously important contribution. The models also contain estimates of ecosystem services and their value to the human components of the system. We can thus test whether the same index (or some other index) is predictive of ecosystem services in the models.

Expected Results

Results of the project will include:

1. A suite of multiscale dynamic models, with particular emphasis on: (1) cross-scale linkages; (2) the global scale; and (3) human system – natural system linkages via ecosystem services.
2. Extensive tests of the models against an expanding database being collected as part of several ongoing projects. Model testing will involve a range of exploratory visualization techniques, appropriate statistical tests, and a multiple criteria model performance index (MPI) that can bring together a range of data quality and testing methods into an overall score. The testing process will probably also lead to significant model reformulation as we learn more about what works and what doesn't.
3. Exercising the tested and calibrated models to answer several important questions about the dynamics and scaling of complex coupled natural and human systems. Issues of modeling efficiency and proper scaling for data and models will be identified through the use of dynamic models and explored in the context of systems whose sentient components perceive and operate on the environment at different scales simultaneously. We will explore more general issues concerning the extent and propagation of aggregation error along the dimensions of time, space, and complexity, with the ultimate aim of constructing a new framework for understanding complex, hierarchically organized systems that respects and exploits biocomplexity.
4. Broad involvement of scientists, students, and stakeholders in both the process of model construction and testing, and using the products of the project via links with GAIM, ongoing international colaborations, and a series of workshops/short courses.

General Project Information

Personnel

We have an integrated team of researchers at the new Gund Institute for Ecological Economics and other departments at the University of Vermont who possess the range of skills necessary to perform the complex tasks associated with the proposed work. (The faculty and staff of the Gund Institute were formerly at the University of Maryland Institute for Ecological Economics.) As a group, they have extensive background and experience in landscape ecology, ecological modeling, hydrology, physics, economics, social psychology, computer software development, and complex systems. We believe that this team is unique. While others would have to form a complex consortium to assemble the skills necessary to perform this project, we have them already assembled and integrated. The project will also train 4 Ph.D. students per year and 1 post-doc per year. More details are given below in the Management Plan.

Time Line

Year One: The first year will focus on 3 major activities: (1) further development of the full suite of models with input from various stakeholder groups. Emphasis here will be on modifications to insure cross-scale consistency and integration of the models and to improve the linkages between the natural and human components of the models via ecosystem services. Individual-based forest models and agent-based human models will be implemented for sites in the BES study area. The integrated GEM/GHSM will be implemented at the watershed scale. The GUMBO model will be made spatially explicit at the global scale (2) assembling the data and modeling modules in a hierarchical fashion making them readily available for testing, calibration and and scaling experiments; (3) analyzing model sensitivity and designing complexity aggregation schemes using the results of the sensitivity analysis.

Products: (1) New versions of the models adjusted for cross-scale consistency and with improved links between the human and natural components via ecosystem services; (2) Improved testing and calibration of site, landscape, and global models, including better general methods to test and calibrate complex models and to understand and display the full range of uncertainty associated with the models; (3) Initial trials of sensitivity and scaling experiments at all scales; (4) Multi-resolution relational database of the Patuxent and Gwynn's Falls watersheds linked to the site and landscape models, with data made available over the Internet through our web page; (5) Publications and web pages on background and theory.

Year Two: During the second year we will: (1) continue data collection and model testing and calibration. By the end of year two, we should have the full suite of models calibrated and tested. While this activity will continue through years 3 and 4 at a reduced intensity, the initial calibrations will be enough to publish results and to continue with the dynamic behavior and scaling experiments; (2) conduct inital trial dynamic behavior experiments (2) further develop aggregation schemes for space, time, and complexity and conduct initial trial scaling experiments across multiple resolutions.
Products: (1) Calibrated and tested models at all scales for use in their own right, and for use in the dynamic behavior and scaling experiments; (2) a suite of aggregation algorithms to be used in the scaling experiments; (3) Publications and web pages on initial model results.
Year Three: (1) perform dynamic behavior experiments to answer questions about ecosystem indicators (vigor, organization, resilience) and explore their relationship to ecosystem services and sustainability at the unit, landscape, and global levels. Identify how scale is related to sustainability and ecosystem services; (2) perform time, space and complexity scaling experiments based on the aggregation schemes developed in year 2; (3) revise models if necessary based on experience with these experiments.
Products: (1) initial conclusions concerning dynamic behavior questions; (2) initial conclusions concerning scaling questions; (3) Publications and web pages on dynamic behavior and scaling questions.
Year Four: (1) Finalize model testing and calibration; (2) Finalize conclusions concerning ecosystem services and sustainability over a range of scales and ecosystems, and their relationships to human well-being; (3) Finalize conclusions concerning scaling in time, space, and complexity and test the generality of our aggregation algorithms .
Products: (1) General conculsions about the dynamic behavior of complex systems; (2) General conclusions about scaling in complex systems and documentation of successful aggregation schemes; (3) Library of model modules available within the SME framework for use by the modeling community at large; (4) A methodology and software tools to estimate ecosystem services, and system sustainability in complex, dynamic ecological economic systems; (5) Publishing and disseminating over the web the final results of the project.

Management Plan

Robert Costanza, the project PI, will serve as team leader, responsible for ensuring that project goals, objectives and annual targets are met. He will assign project components to the most appropriate researchers, coordinate their integration, and provide the overall strategy. Dr. Costanza will also contribute his substantial skills and experience in modeling, theoretical ecology, and natural-human system integration. Weekly meetings of the research team to assess progress and problems will help keep all research on track.

While the research team will function very much as a team, with all members contributing to the overall project, specific participants will take the major responsibilities for specific elements. Jon Erickson, Joshua Farley, Matthew Wilson, and Roelof Boumans will be responsible for further development and integration of the human system components of the models. Jon Erickson will lead the development of the agent-based model at the neighborhood scale and participate in the further development of the GHSM and GUMBO. Roelof Boumans and Breck Bowden will lead further development of the GEM unit model and the ecological modules of GUMBO. They will also be responsible for linking the ecological and socio-economic models and implementing the spatially explicit version of GUMBO. Matthew Wilson will lead further development of the social capital components of the models. Drs. Wilson, Boumans, and Farley will serve as our main liasions with the social scientists on the LTER Baltimore Ecosystem Study, obtaining the relevant data from this group, and working to coordinate their research efforts with our data requirements. Alexey Voinov and Breck Bowden will further develop the landscape models and manage the spatial calibrations and scenario runs. Ferdinando Villa will lead further development of the software and statistical methods for model testing and calibration. Thomas Maxwell will be responsible for the further development and support of the SME software package, including the Java-based interface and Simulation Module Markup

Language. Marta Ceroni, Jennifer Jenkins and Jon Erickson will be responsible for development of the forest IBMs for specific sites. Graduate students and post-docs will be assigned to specific researchers to help meet project demands consistent with their own interests and skills.

Such a complex project as this one will benefit greatly from outside peer review and frequent feedback. We will open our weekly project meetings to the University of Vermont community and any other interested scientists. We will also structure problem-based short courses around various aspects of the project to insure broad student and faculty participation. Preliminary results will be published as working papers, both electronically and in hard copy, in an effort to solicit feedback from other researchers. To make our research available to the broader scientific community and maximize the potential for immediate peer review, Dr. Voinov will keep all important research results posted on the Web.

Education and Outreach

Applied transdisciplinary research and education is the explicit goal of the Gund Institute, and is essential to understanding the complex interactions between the human and ecological systems. We make substantial efforts in education and outreach in virtually all of our projects. This project will extend our ongoing efforts in several ways:

1. Four full-time graduate students will participat in this project for each of four years. We will make every effort to ensure that these students achieve an understanding of and involvement in the entire project, regardless of their previous disciplinary training.
2. Problem-based "atelier" short courses at the University of Vermont will be constructed around various aspects of the project to insure broad student, faculty, scientist, and stakeholder participation. Members of the GAIM and ESSP networks and the BES study will be active participants in these courses/workshops, along with our international partners at ICIS. Two courses/workshops per year are planned as part of the process.
3. As a member of the National Computation Science Alliance's (NCSA) Environmental Hydrology Application Technology team, we are developing the ecosystem modeling component of the Alliance's Environmental Hydrology Workbench. We are also collaborating with the Maryland Virtual High School Program to make realistic ecosystem modeling available to students, which has led to our participation in the Core Models and River Web programs. These projects are designed to create learning tools and collaborative frameworks for education of 21st century citizens to participate actively in science-based, informed debate and policy-making about the management of natural resources vital to their communities.
4. As part of the Baltimore Ecosystem Study (BES), we are committed to the education of students from K through college, to show them how research is done and to make them aware of the availability of careers in environmental science. The BES educators are interacting with teachers and schools to help in their science curricula. Neighborhood revitalization and planning efforts can use high quality ecological data and our modeling results to work toward their goals. Our models will help people see how their environment is changing, and assist them in deciding how to plan and react to those changes. Through BES, we will work closely with the school systems, involving students in research and helping train teachers in the methods for teaching the sciences. This project will greatly expand our efforts in this area.
5. As part of our joint NSF/EPA Whole Watershed Health and Restoration project, we held a series of stakeholder workshops aimed at using the landscape models for enhancing shared understanding. We will continue via this project to use the PLM and GFLM models and their associated databases to test various policy scenarios for both a largely rural/suburban watershed (PLM) and a largely urban/commercial watershed (GFLM). This allows us to combine scientific input with stakeholder input to develop politically, socially, and academically credible results. The workshops thus serve as both education and outreach. The current proposal will further improve the PLM and GFLM models, and contribute to our efforts to develop them into accessible, effective watershed management tools. As part of this project we will also extent this workshop-based approach to the global scale.