Current Problems and Future Directions in Computational Science for Natural Resource Management

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ABSTRACT

Natural resource managers must cope with a host of complex problems ranging from routine tasks to urgent problems such as the control of wildfires, emerging wildlife diseases, and non-native species. Recent advances in miniaturization, computing power, remote sensing, and modeling are revolutionizing the science of natural resource management. But these advances also bring many challenges. The need for information management and communication, dynamic models, and real-time monitoring places increasing demands on legacy data structures and over-burdened networking infrastructures. To meet these demands, natural resource managers require access to high-performance computing tools and improvements in data storage, communication, and analysis. Computer scientists are needed who can collaborate with natural resource managers and modelers to develop novel solutions. Here, we highlight several key problems in resource management that represent exciting opportunities for computer scientists and engineers in search of challenging practical problems.

INTRODUCTION

Natural resource managers are faced with the difficult task of balancing the needs of complex, dynamic ecological systems with the competing demands of social, political, and commercial stakeholders. Natural resources include wildlife and habitats that provide significant recreational (e.g. hiking, fishing, hunting), economic (e.g. timber harvesting, gene mining), aesthetic (e.g. scenic landscapes) or functional (nutrient retention, flood control) value. The ecological and environmental processes that govern functioning ecosystems are difficult to manage because they involve multiple components that operate over broadly disparate temporal and spatial scales. To manage the components of natural reserves, biologists have traditionally relied on “rule of thumb” strategies based largely on what has worked in the past. This data-driven approach has largely been replaced by model-driven strategies, which attempt to forecast system behavior under alternative management scenarios. Such models are frequently wedded to emerging technologies for data collection and monitoring, such as real-time remote sensing and GPS. But while these advances greatly improve the temporal and spatial resolution of ecological information, they also generate large volumes of data. This flood of information increases the demand for efficient approaches to data analysis, storage, and communication. At the same time, the evolution of approaches based on disparate technologies and computing platforms complicates the sharing and integration of data from different sources.

As resource managers struggle to cope with these challenges, they have turned to computational science for solutions. The rapid advance of software and architectures designed to exploit improvements in networking, interoperability, and data management have revolutionized natural resource management. The changes to natural resource management in many ways mirrors that of molecular biology, whose dependence on high-performance computing is well known. For example, models of biochemical networks have been expressed as stochastic Petri nets (SPNs), a mathematical formalism developed in computer science[1]. Another example is the use of high-performance algorithms to improve the computationally intense sequence comparisons used in molecular phylogenetics[2]. As a consequence of computerization, management programs have rapidly grown in size, complexity, and computational power. Modern resource management depends more and more on computational support such as Geographic Information Systems (GIS) for interactive computational steering[3,4], high performance computing for integrated system modeling[5] as well as geographically distributed grid computing technologies such as GLOBUS (www.globus.org), Netsolve (icl.cs.utk.edu/netsolve) and Internet Backplane Protocol (http://loci.cs.utk.edu/ibp/index.php). More recently, the National Science Foundation’s cyber-infrastructure initiative aims to promote next generation (grid-based) information infrastructures to accelerate scientific discoveries. These advances have increased the speed and sophistication of models, allowing managers to tackle large, complex problems that a few years ago would have been unmanageable (see Figure 1 for an example). However, the field of resource management has only scratched the surface of computational approaches.

While applied computer science has a strong tradition of collaboration with the engineering and physical sciences, the lion’s share of its involvement with applied biology is limited to solving the data management and analysis problems of molecular biologists. For example, computer scientists are actively engaged in improving techniques for managing the large amounts of data produced by the high-throughput sequencing technologies used in the field of genomics. Natural resource management is currently undergoing a rapid transformation to highly computerized environments, similar to that experienced by molecular biology in the past decade. As a consequence, there is great need for collaboration between CS professionals and natural resource managers. In the following series of sidebars, we highlight several key problems, current approaches, and possible future solutions that computational science may afford.

The challenges faced by natural resource managers can be loosely classified into three areas: Data Management/Communication, Data Analysis, and Optimization and Control. Each of these areas contains a diversity of problems, many of which are of great economic, social, and political importance. However, a particular problem may involve all three areas. For example, solutions to the control of exotic species depend on information about the occurrence and spread of organisms (Data Management/Communication), understanding spatial and temporal patterns of invasion (Data Analysis) and developing strategies to manage populations of exotic species (Optimization and Control).

Technological advances and computerization create the need for the efficient data management. Satellite imagery, GPS, remote sensing, and GIS generate vast amounts of environmental information that must be processed, analyzed and stored. Spatially-explicit or geo-referenced data are particularly information dense, with each point on a map (or 3-dimensional volume) representing a data vector that can include environmental, ecological, and geographic information. The sheer volume of digital data creates challenges for organization, storage, and retrieval. Ecoinformatics (see sidebar) is the use of computational methods to manage and study ecological data[6]. Herein lies many opportunities for computer scientists and engineers skilled in data search and archiving approaches and in building the software and protocols needed for data management.

There is also a need for improved search and storage algorithms. For example, spatial data vectors are not easily represented as points in space. Object-oriented approaches to data representation are an obvious solution but need not be restricted to traditional hierarchical strategies. Spatial data matrices are often sparse and characterized by complex distribution patterns. Indexing strategies that account for the structural aspects of data manifolds, such as R-trees and geometric optimization algorithms, hold promise here[7]. Resource managers would also benefit from improvements in file compression and software capable of analyzing terabyte-size data files. Current storage approaches used for GIS, vector, and raster data are not necessarily the most efficient or most accessible.

GIS-Enabled Dynamic System Modeling

Most natural resource issues have a significant spatial component, such as the distribution of land use in a watershed, the proximity of human populations to a reserve, or the degree of habitat fragmentation in an ecosystem. Because of this, GIS technology is used extensively to visualize, analyze, and model natural resource data for management and problem solving[8]. However, the integration of GIS with dynamic models is not an easy task because of the burden of specialized data formats and management tools used to process georeferenced data. GIS was originally designed to expedite the processing of spatial objects on a digital map. Therefore, compound data formats were created to store geographic information for rapid indexing, georeferencing, and visualization. Also in order to conveniently deal with user input, event based programming (using visual programming language such as Visual Basic) is generally preferred. This in turn brings additional overhead to a GIS system. Good examples are the products of Environmental Systems Research Institute (ESRI; www.esri.com/), which are developed using component-based building-blocks called ArcObjects.

The lack of a light-weight data format for modeling and performance tuning is another obstacle to incorporating GIS into dynamic models. Dynamic modeling frequently has a strong temporal component and is computationally intensive. Because GIS data formats and management tools are not designed for dynamic modeling, a convenient and feasible approach is to design a custom data format to extract and store only specific information. There is a growing trend to provide online user services, such as the web-based user interaction tools provided by ArcIMS. In these environments a light-weight data format is also desirable to mitigate the performance bottleneck associated with web-based services and geo-referenced data formats. However, it is not practical to require major GIS vendors to provide customized data formats for natural resource management problems. Figure 2 illustrates a software architecture for GIS-enabled dynamic modeling.

High performance computing for integrated system modeling and spatial control:

To better understand the behavior of natural systems, resource biologists use models to simulate the processes that control ecological systems on different spatial and temporal scales. Resource managers use the output of these dynamic models to project the behavior of natural systems for planning purposes. Because modern computer hardware designs exploit the performance gains associated with parallelism, the software used in modeling should also embrace parallel data structures. Component-based architectures are a natural choice for modeling complex systems on high performance computational platforms. However, there is a common misunderstanding that “master-slave” models can support “embarrassingly” parallel computing in many resource management applications, such as statistical analysis and uncertainty analysis. This statement is only valid for small-scale simulations. Today’s mid-sized cluster usually has over 100 processors and is capable of executing hundreds of concurrent simulations. For this reason the simple master-slave model is no longer the preferred approach for such analyses. A hierarchical computational model and dedicated coupling component are needed to ensure high performance and scalability of integrated system simulations. This is especially true for applications running on high-end computers, which generally have thousands of processors. Moreover, as simulations become larger and longer users must cope with additional software design issues such as recovery-oriented computing (http://roc.cs.berkeley.edu/) and fault-tolerant computing (http://www.crhc.uiuc.edu/).

Spatial control is another application that demands high performance computing (Figure 2, 3). Spatial control refers to the field of mathematics concerned with regulating the behavior of complex, spatially explicit systems[9]. Resource managers use the techniques of spatial control to develop management strategies for controlling such problems as wildfires (Figure 2), invasive species, and wildlife diseases such as rabies (Figure 3). Alternative control strategies are first implemented in models to test their effectiveness prior to use in the field. From a software design aspect, spatial control can be developed as an independent component on top of integrated system models (Figure 1).

Grid Computing and Cyber-Infrastructure

Grid computing[10] provides researchers with access to geographically distributed high-performance computers and scientific software packages (Figure 4). The main thrust of grid computing focuses on the accessibility and security of the grid infrastructure and the general structure of grid-based applications[11]. However, the cyber-infrastructure for natural resource management must focus on the development of customized services to support the entire life-cycle of scientific discovery, ranging from real-time data collection (via sensor networks, satellite images, GPS, etc.; Figure 2), to data transmission, archival, and storage (Figure 4) as well as the dynamic models used as decision support tools for adaptive management (Figure 3). Currently a few cyber-infrastructure applications exist for cross-disciplinary scientific research, such as the TeraGrid Project (www.teragrid.org) and the EPIC project (www.eotepic.org). From the computer science perspective, two major components of cyber-infrastructure are required before resource managers can take full advantage of distributed (high performance) resources. First, an *n*-tier software architecture is needed to expedite the flow of data across a diverse set of services including interactive graphic user interfaces (i.e. event-driven visual programming), metadata (i.e. relational databases), and dynamic system multi-modeling, as well as non-interactive, fault-tolerant high performance backend computation. The architecture should also provide convenient methods to implement data flows through both a logical view (management) and a technical view (software). Second, a system for “management intelligence” is needed that consolidates observation/field data and modeling results, enables reporting and projecting the fundamental behaviors of natural resource system, and analyzes data to find optimal solutions to management problems (Figure 2). A successful cyber-infrastructure should provide several predefined service modules, which can either be used by natural resource managers without any adjustment or serve as a template for client-specific problems.

Conclusions and future challenges:

Recent collaborations between computer scientists and natural resource managers have led to significant progress in overcoming the obstacles we have discussed. Yet such pioneering work is only the beginning and numerous challenges remain. Among these are issues arising in many fields dealing with 1) multi-scale or hybrid modeling; 2) tying realistic decisions to the diverse, large data sets that arise from advances in sensor technology; 3) developing the potential for real-time responses to rapidly emerging issues such as disease management; 4) providing usable results at the desktop while utilizing high performance computational resources; and 5) using models to develop effective and efficient monitoring programs. We summarize here some of these future challenges with the objective of encouraging computational scientists to consider applying their expertise to find solutions.

A host of problems faced by resource managers involve multiple processes that operate over vastly different spatial and temporal scales. To integrate their approach to solving such complex problems, resource managers adopt a two-tiered policy, in which management actions are divided into tactical and strategic components. For example, Everglades management requires decisions about short-term, day to day control of water flows while considering strategic decisions about building and removing control structures that would occur over several decades[12]. Computational tools which foster the linkages between such two-tiered approaches to management are essentially non-existent. Options for the simultaneous consideration of these multi-scale management issues, that account for constraints imposed by decisions at one scale on another, could feasibly be addressed in a parallel computational framework. Bringing this to managers would require appropriate software that generalizes specific land management problems that recur around the world.

With advances in sensor technology, access to real-time environmental data is becoming more common (Figures 1, 2). Emerging diseases of wildlife that impact humans, such as avian flu, are just one area in which rapid assessment management options can be critical[13]. But the efficiency and speed with which models can be combined with highly dispersed data sets depends on access to appropriate computational tools. The GIS-enabled management decision support tools described earlier (Figure 2) would provide the capability for rapid responses, in a spatial context, to quarantine, vaccination, and culling strategies for these situations. As some of these situations have global implications and involve global networks of scientists and managers, these decision support tools would ideally be available for large numbers of distant collaborators, requiring a grid computing infrastructure to manage such collaborations (Figure 4). Similar issues arise in regional plans which have local management implications. One example is water management in much of the western US in which regulatory decisions, typically derived in part from extensive legal negotiations, put direct constraints on local water use and development opportunities[12].

Model selection is a major challenge for resource managers. As data sets are generally sparse, (i.e. having many missing or zero values), they present a variety of patterns to which models might be compared. What's more, decisions based on these models may be subject to legal scrutiny motivated by the often conflicting views of the different stakeholders affected. Modern computational tools offer great promise as an aid to model selection, but have yet to be employed in more than a few cases. Lifemapper.org provides one example in which distributed resources were mobilized to compare large numbers of possible environmental variables with species presence/absence data. Here, GARP[14] (genetic algorithm regression procedure) is used to choose an appropriate component of biodiversity measurement. Recent arguments for the use of pattern-oriented approaches in ecology[15] indicate a need for general model selection tools for diverse types of spatial models, ranging from those built within a GIS to agent-based models. Such computational tools are needed to confront alternative models with data and to choose appropriate parameters for these models from limited data, for example by applying optimization approaches (see Optimal Control sidebar).

The spatial control issues mentioned above are not as yet coupled with adaptive management methods. In adaptive management, models are used as an inherent part of the management framework to reduce uncertainty about system responses. The objective is to limit the enormous control space to one that is feasibly analyzed by a combination of grid and desktop tools. Another objective of spatial control is to guide the development and use of spatial monitoring systems (Figure 3). An example is using models to find optimal strategies for allocating limited funds and management resources (see Fire Management sidebar) while maintaining the capacity to respond to emerging issues such as disease outbreaks[16] (Figure 3).

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SIDEBARS

OPTIMAL CONTROL

Resource managers are perennially faced with limited manpower, funds, equipment, and supplies that must be distributed among a laundry list of daily tasks. Optimal control approaches combine mathematics, biology, and economics to identify the best strategy for a given goal and set of constraints[9,17]. Figure 2 shows the application of optimal control to fire management, while Figure 3 shows a disease control application. Workloads for many tasks, such as harvesting and erosion control, may be periodic or seasonal. But workload scheduling must also accommodate unplanned demands on time, supplies and manpower such as catastrophic fires, floods, and the arrival of new exotic species or disease. Traditional approaches to managing such tasks are data-driven and goal oriented, though often goals are vague or ill-defined. Optimal control models attempt to find the most efficient control strategy for allocating limited management resources, given constraints on time or effort. However, few software tools are available for implementing optimal control approaches. There is a particular need for spatially explicit models that can examine the influence of processes that operate in 2 and 3 dimensions. For example, work is needed on models based on Pontryagins's optimal control theory (Sethi and Thompson 2000) which may consider space as continuous (e.g. with dynamics described by partial differential equations) or discrete (e.g. using difference equations). Spatial explicitness adds a computational burden to models (Figure 2) and such models would benefit from parallelization, high-performance computing, and the development of lightweight data formats.

FIRE MANAGEMENT

Fire management is a complex problem that involves forecasting fire frequency and magnitude as well as seasonal demands for equipment, fire crews and the aircraft used to spot and fight fires in rugged terrain[18]. Resource managers must coordinate fire monitoring and control with municipal and regional fire management agencies. Often multiple organizations must share fire-fighting resources such as water trucks, aircraft, and work crews. An important problem in fire management is therefore how to optimally manage limited resources. As an aid to forecasting, resource managers use spatially explicit models that replicate vegetation dynamics and other processes that govern fire outbreak and spread (Figure 2). Such models allow researchers to test the effects of different variables, such as the age and density of stands, topography, vegetation type, and short and long-term weather conditions. The goal is to improve the accuracy of fire forecasts and to develop effective control strategies. To this end applied ecologists have used linear and non-linear programming to identify optimal solutions. Yet, the complexity of models is increasing as technological advances, such as satellite imagery, increase the scale and resolution of spatio-temporal data. These improvements create greater demands for efficient modeling and processing. Here we see opportunities for computer scientists skilled in parallelization and concurrency in computation.

DISEASE AND INVASIVE SPECIES

Resource managers consider the control of disease and invasive species a top priority[19,20]. The global transportation network for people and commercial goods permits the rapid movement of organisms around the world. International commerce facilitates the intentional and unintentional introduction of exotic species, which may become local pests. Under the right conditions, exotics can become invasive to the point of threatening local and regional resources. For example, the wooly adelgid, an aphid-like insect pest native to Asia, is causing extensive damage to native hemlock forests in the southeastern US[21]. Exotic species can also introduce disease pathogens. Imported Asian chestnut trees brought the chestnut blight fungus to North America, which then devastated the American chestnut tree. There are many opportunities for computer scientists to improve the management of exotic species. Resource managers need tools for cataloging, tracking, and monitoring existing problem species. These tasks are complicated by the need for communication and data sharing among the many local, regional, and national agencies and organizations that deal with exotics, such as the US Fish and Wildlife Service (www.fws.gov). In addition, resource managers desperately need information on how to effectively control invasive species without endangering populations of native species. There is a great need here for high-performance solutions. For example, goal oriented computational approaches that search for optimal or extremal solutions, while useful, have yet to fully exploit the benefits of parallelization (Figure 3). Examples include numerical optimization (e.g. linear and nonlinear programming) and evolutionary computation that involves guided random search and parallel processing.

ECO-INFORMATICS

Advances in embedded computer technology and remote sensing have greatly expanded our ability to collect environmental data. Ecoinformatics requires the development of computational methods for studying the structure, function, and evolution of species, communities, and ecosystems. Ecoinformatics also requires the development of methods for managing large amounts of environmental data. The National Science Foundation supports several research groups (Table 1) who are developing data management solutions. Generally the goal of these groups is to establish networking infrastructures that integrate data acquisition, storage, and analysis. Other goals include advancing sensor and embedded computer technology and improving access to remotely sensed data. For example, CLEANER is investigating the use of networks of autonomous underwater vehicles for data collection. Related technologies include integrated sensor microsystems, pervasive computing, and wireless communication.

TABLE 1: NSF Funded Collaborations in Ecoinformatics

Organization	URL
Collaborative Large-scale Engineering Analysis Network for Environmental Research	cleaner.ce.berkeley.edu
Consortium of Universities for the Advancement of Hydrologic Science	www.cuahsi.org
National Ecological Observatory Network	www.neoninc.org

Ocean Observatories Initiative	www.orionprogram.org
Science Environment for Ecological Knowledge	seek.ecoinformatics.org

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FIGURE CAPTIONS

Figure 1: A component-based architecture for integrated system modeling with spatial control. Spatial control can be implemented on top of integrated system modeling. Here, a job scheduler allocates computing resources for a multi-component fire model. Different optimal control schemes can be implemented via changes to job scheduling and executed by corresponding simulation drivers. The job scheduler also interacts with a computational steering console, through which managers can "manually" chose an optimal scenario and enforce the underlying simulation to take a specific path.

Figure 2: A software architecture for GIS-enabled dynamic modeling. GIS provides convenient interactive methods for visualizing data and preparing reports. GIS generally rely on compound data formats to represent and manipulate data. Such compound formats create a burden for dynamic models that are computationally intensive. Therefore, a *data extraction/conversion toolkit* is often necessary to 1) transform native data into proprietary formats for geoprocessing or visualization, and 2) exchange data between the GIS and a dynamic modeling package. This example shows how multiple georeferenced data layers can be converted for use in models using different frameworks. The use of a data extraction/conversion toolkit frees the modeler to use standard programming languages (such as C++/C/Fortran) for dynamic modeling and high level languages (such as script languages) for GIS related programming. It also facilitates the use of high performance computing resources which otherwise would be unavailable within a traditional GIS.

Figure 3. Optimal control of disease: Rabies in Ohio. The spread of rabies is an significant public health issue. In the Midwestern US, raccoons are an important carrier of rabies, which spreads from an infected animal (depicted by the raccoon marked with the letter 'I') to susceptible uninfected individuals ('S' raccoons in figure) by direct contact[22]. To control the spread of rabies into Ohio from Pennsylvania and West Virginia, resource managers release small

food packets that contain an oral vaccine. Uninfected raccoons that eat the vaccine become immune to the disease. By dropping the packets from an airplane ahead of the advancing disease front, managers hope to slow its rate of spread. Vaccination success is determined via monitoring the raccoon population near the wave front. Such efforts are constrained by limits on funding, manpower, and other resources and researchers are now investigating the use of optimal control models to determine the most effective strategy.

Figure 4: A simplified cyber-infrastructure for natural resource management.

Grid-based services enable real-time data collection and storage and the use of dynamic modeling to facilitate decision support for adaptive resource management. As shown, the cyberinfrastructure facilitates the sharing of data and computing resources such as processing power and storage. Data and associated services are the fundamentals that allow natural resource managers to deliver reader-friendly multidimensional reports. Web portals and graphic user interfaces allow users to interact with such reports using the Internet.