Computational Sustainability: Computational Methods for a Sustainable Environment, Economy, and Society

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The dramatic growth in humanity's use of natural resources over the past century is reaching alarming levels, threatening our planet and the livelihood of future generations. Our Common Future, the seminal report of the World Commission on Environment and Development, published in 1987, raised serious environmental concerns about the state of our planet. Our Common Future was also forward-looking, introducing for the first time the notion of *sustainable development*: *development that meets the needs of the present without compromising the ability of future generations to meet their needs.* The concerns raised by Our Common Future were reiterated by the United Nations Environment Program in its fourth Global Environmental Outlook report published in October of 2007 (UNEP 2007) and by the United Nations Intergovernmental Panel on Climate Change (IPCC 2007). For example, the fourth Global Environmental Outlook report stated that "there are no major issues raised in Our Common Future for which the foreseeable trends are favorable."

The development of policies for sustainable development translates into decision making and policy making problems concerning the management of our natural resources involving significant computational challenges that fall into the realm of computing and information science and related disciplines (e.g., operations research, applied mathematics, and statistics). The new field of *Computational Sustainability* brings together researchers in these fields to develop new computational models, methods, and tools to help manage the balance between environmental, economic, and societal needs for a sustainable future.

In this short paper, we provide examples of computational sustainability problems arising in different domains, ranging from wildlife preservation and biodiversity, to balancing socio-economic needs and the environment, to large-scale deployment and management of renewable energy sources. We also outline several broader research themes in computational sustainability.

COMPUTATIONAL CHALLENGES IN SUSTAINABILITY

Sustainability and sustainable development concerns the interactions between environmental, economic, and societal needs. In this section we consider examples of computational problems in the context of these different dimensions of sustainability.

Biodiversity and Species Conservation

The reduction and fragmentation of natural habitat due to deforestation, agriculture, urbanization and land development is a leading cause of increased rates of species decline and extinction. A strategy to increase the chances of species viability is to protect habitat through the creation of biologically valuable sites or reserves. Examples include the National Wildlife Refuge System, managed by the U.S. Fish and Wildlife Service, national parks, as well as conservation reserves established by private groups such as the Nature Conservancy or The Conservation Fund. Given the limited resources available for conservation, it is critical to choose sites carefully. From a mathematical point of view, *the site selection or reserve design problem* (Ando et al. 1998, Moilanen et al. 2009, and Polasky et al. 2008) concerns the selection of sites optimizing certain criteria (e.g., habitat suitability for certain species), while satisfying one or more constraints (e.g., budget). In recent years biologists have also recognized the importance of actively combating habitat fragmentation, leading to considerable interest in so-called *conservation corridors*, which are continuous areas of protected land that link zones of biological significance. The design of conservation corridors is a special case of the site selection problem: the objective is to design connected corridors that are made up of the land parcels that yield the highest possible level of environmental benefits (the ``utility") within the budget available (Onal and Briers 2005, Williams et al. 2005). We have recently formulated this problem mathematically as a so-called *connection sub-graph problem* (Conrad et al. 2007; Gomes et al. 2008). As a particular application, we considered the design of wildlife corridors for grizzly bears in the Northern Rockies, enabling movement between the three core ecosystems: Yellowstone, Salmon-Selway, and Northern Continental Divide Ecosystems, spanning 64 counties in Idaho, Wyoming, and Montana. This application corresponds to a large-scale optimization problem posing significant demands on current computational methods. In order to scale up solutions, a deeper understanding of the underlying problem structure is required. We developed a budget constrained utility optimization approach using a hybrid constraint-based mixed integer programming approach that exploits problem structure. Our results show that we can dramatically reduce the cost of large scale conservation corridors --- by over an order of magnitude --- compared to existing, more ad-hoc, corridor design strategies.

Further complexity in the site selection and corridor design problems results from considering different models for land acquisition over different time periods (e.g., purchase, conservation easements, auctions), dynamic and stochastic environments, and multiple species. For example, in order to preserve bird habitats and design bird corridors, a good understanding of hemispheric-scale bird migrations is required, with complex population dynamics, across different climate and weather systems and geographic topologies. Modeling such complex species distributions and developing appropriate conservation strategies requires the development of new large-scale stochastic optimization methods. Moreover, to obtain the right model parameters and determine current species distribution, machine learning and statistical techniques are required to analyze large amounts of raw species data (Dudik 2007; Dietterich 2009; Elith et al. 2006; Kelling et al. 2009; Munson et al. 2009; and Phillips et al. 2004).

Natural Resource Management

We now consider an example about the concerning situation of the state of the world's marine fisheries: The biomass of top marine predators is estimated to be one-tenth of what it was half a century ago and is declining (Worm et al. 2006). As a result of overfishing, pollution and other environmental factors, important marine species have gone extinct, with dramatic consequences in terms of the ocean's ability to filter nutrients. Researchers believe that the collapse of the world's major fisheries is primarily the result of the mismanagement of fisheries (Clark 2006; Costello et al. 2008). There is therefore a clear urgency to find ways of managing fisheries is a sustainable manner. A particular management approach that has been shown effective in terms of counterbalancing overharvesting involves limiting the total allowable catches per species, combined with permits to harvest specific quantities of fish, known as individual transferable quotas (Costello et al. 2008; Heal and Schlenker. 2008; Worm et al. 2009). Complex dynamical models, as developed as part of dynamical systems theory, can be used to identify the optimal annual amount of fish that can be harvested in a certain fishery, taking into consideration re-generation rates of species, carrying capacity of the habitat, discount rates, and other parameters.

Dynamical systems theory provides tools for characterizing the dynamics and long term behavior of systems as a function of its system parameters, providing insights into the nonlinear system dynamics, identifying patterns and laws, in particular, bifurcations (Ellner and Guckenheimer 2006; Strogatz 1994). A bifurcation occurs when small changes in the parameter values of the system (e.g., the rate of fish harvesting) leads to an abrupt qualitative change (e.g., the collapse of a fishery).

In addition to non-linear dynamics, our problems also involve making *decisions* such as the amount of fish to harvest, often combining continuous and discrete variables. This leads to a class of *hybrid dynamical optimization models* (Clark 1976; Conrad 1999). These models in principle provide information on optimal harvesting strategies but finding such strategies is computationally hard. One can simplify the problem by only considering certain classes of harvesting policies. For example, traditional approaches have focused on so-called constant escapement policies. Our initial analysis indicates that in discrete-time models, periodic policies can outperform constant escapement policies (Ang et al. 2009; Ermon et al. 2009). Furthermore, our computational results provide new insights into how different model parameters, e.g., the discount rate and cost elasticities, dramatically affect the optimal policy strategy.

Balancing Socioeconomic Needs and the Environment

We now consider an example that highlights another dimension of sustainable development. One of the members of our Institute for Computational Sustainability at Cornell University, Chris Barrett, has extensively studied the socioeconomic interrelationship between poverty, food security, and environmental stress in Africa (Barrett et al. 2007). Barrett is interested in understanding the links between resource dynamics and the poverty trap in small holder agrarian systems. In particular, we consider pastoral systems in East Africa (Luseno et al. 2003). Pastoralists maintain herds of animals such as cattle, camels, sheep, and goats. Due to the high variability in rainfall they migrate looking for water and forage resources, traveling sometimes as far as 500 km. We would like to obtain a predictive model of the migratory patterns and the decision models of pastoralists. We are using machine learning methods to determine the structure and estimate the parameters of these models, based on field data concerning households, water points, and climate patterns. The goal is to help policy makers predict the effects of various potential policy interventions and environmental changes, with the goal of improving the livelihood outcomes of thousands of pastoralists in these regions. The project brings new technical approaches for large structural dynamic discrete choice problems, providing computational models that permit both descriptive study and predictive policy analysis (Toth et al. 2009).

Other computational sustainability topics in this context include the design of automated decision support tools for humanitarian aid in response to catastrophes, famines, and natural disasters in developing countries (Barrett et al. 2006, 2008, 2009). The design of such systems also requires the development of intuitive and user-friendly interfaces for use by general aid workers.

Increasing Energy Efficiency and Renewable Energy

Last but not least we mention the implications of climate change on environmental, economic, and social systems that have led, for example, to major efforts concerning energy, including changes in energy policy in many industrial countries. From a computing and information science point of view there are tremendous opportunities to help increase energy efficiency, such as through the design of control systems for smart energy-efficient buildings, vehicles, and appliances. This research combines work on sensor networks with intelligent controls. For example, in smart buildings, heating and cooling can be regulated based on real-time office occupancy information obtained using motion sensors (Osterlind et al. 2007).

The deployment of large sensor networks is becoming a key tool for environmental monitoring. There are several computational challenges concerning the design of such networks. For example, when using wireless networks to monitor spatial phenomena, the selection of the best sensor placement in order to maximize the information gain while minimizing communication costs is a complex optimization problem requiring new solution techniques (Krause et al. 2006, 2008).

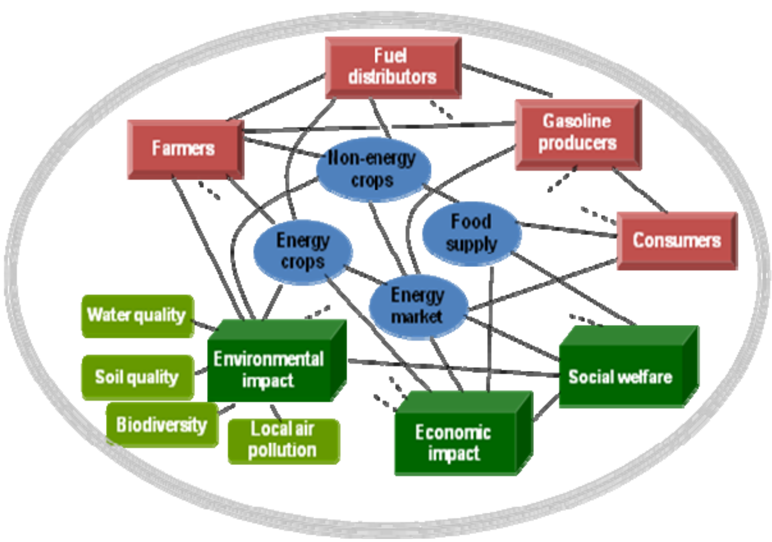

FIGURE 1 Interacting components for biofuel analysis.

In addition to increasing energy efficiency, the development of renewable energy sources that are cleaner and generate little or no carbon can have an even greater environmental impact. In recent years there has been considerable technological progress in the area of renewable energy sources, such as biofuels and biomass, geothermal, solar, and wind power, in part fostered by government incentives. For example in 2007, the Energy Independence Act was signed into law, a broad energy bill setting higher fuel economy standards for vehicles and requiring an annual production of 36 billion gallons of renewable fuels by 2022, a fivefold increase from current ethanol production levels. The logistic and planning of such a large-scale domestic based biofuels production system leads to complex stochastic optimization problems --- variants of the so-called *facility location problem* --- given its large-scale stochastic input (e.g., feedstock and demand) and the need to consider the dynamics of demand and capacity (Shmoys 2004, Shmoys and Swami 2006). Finding good solutions for such models can make the difference between economic viability and failure.

A broader question concerns the development of computational models to shed light on the overall impact of an ethanol based industry considering the interactions between the different agents directly or indirectly involved in the process such as households, landowners, farmers, ethanol producers, regular gasoline refiners, food producers, and the environment (greenhouse gas emissions, water, soil erosion, etc.) (Searchinger 2009; Bento and Landry 2009). The challenge is to develop realistic models within the macroeconomic framework of so-called general-equilibrium models, in a way in which meaningful solutions can still be computed, without imposing strong (unrealistic) assumptions. See Figure 1. The traditional approach in model-formulation has focused on models in which convexity assumptions have forced unique equilibria, or at the very least, that the set of equilibria are themselves convex. This has made their efficient algorithmic solution possible, but unfortunately such models do not capture key aspects of the systems. Answering these questions will require the development of more complex computational decision models through a collaboration between resource economists, environmental scientists, and computer scientists.

Finally, a key issue in environmental policy is how to balance individual interests with the common good, especially when common property resources are involved, as was so eloquently noted by Garrett Hardin in his 1968 *Science* paper on the "Tragedy of the Commons." Game theoretic models play a key role in modeling such interactions and the effect of competing interests. For example, in the context of natural resources or climate change, on the international level, economic incentives may play a big role in whether a country is motivated to enter an agreement and then abide by it. Other incentive-based policies can help facilitate sustainability challenges on a smaller scale. For example, the introduction of novel markets for various kinds of land conservation activities, poses interesting mechanism design problems. Research on capturing multi-agent settings requires the development of multi-agent equilibria models and the design of effective mechanisms and policies for the exchange of goods, paying particular attention to their computational properties.

RESEARCH AREAS AND THEMES

Research in computational sustainability involves a number of different areas in computing and information science and related disciplines. Figure 2 highlights some of these areas and interactions. Figure 3 emphasizes the different levels of complexity in computational sustainability, often leading to unique and complex large scale problems, involving large volumes of data, in highly dynamic and uncertain environment, with many interacting components.

From a computational complexity point of view, computational sustainability problems are often NP-hard or worse, and problem size scales to several orders of magnitude. Given the various sources of complexity of computational sustainability problems, their study requires a fundamentally different approach than the traditional computer science approach driven mainly by worst-case analysis. We propose a perspective that has not traditionally been pursued within computer science, which we refer to as *science of computation*: in this perspective, computational problems are viewed as "natural" phenomena and therefore as problems of the natural sciences instead of purely as mathematical abstractions or artifacts. In other words, in order to capture the structure and properties of complex real-world sustainability computational problems, a scientific methodology is required in which principled experimentation plays as prominent a role as formal models and analysis, to explore problem parameters and hidden problem structure and alleviate the worst-case intractability of many sustainability problems (Gomes and Selman 2007).

As our examples showed, the range of problems that fall under Computational Sustainability is rather wide, encompassing computational challenges in disciplines as diverse as ecology, natural resources, atmospheric science, and biological and environmental engineering. Research in Computational Sustainability is therefore necessarily an interdisciplinary endeavor, where scientists with complementary skills must work together in a collaborative process.

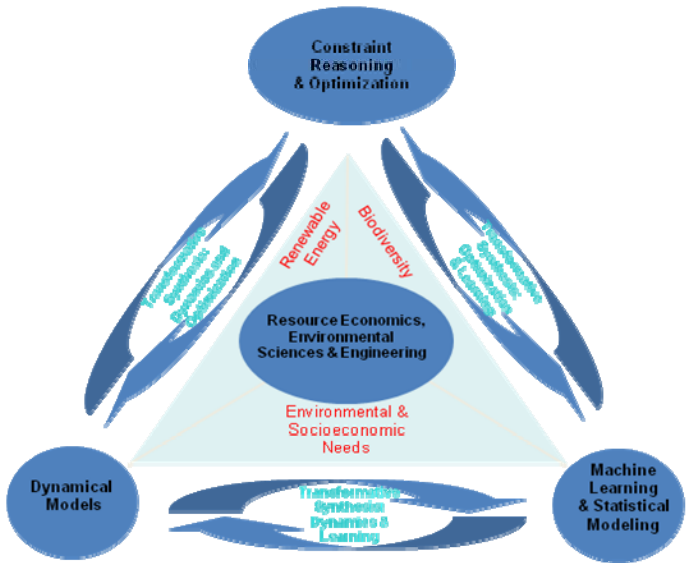

FIGURE 2 Research themes in computational sustainability.

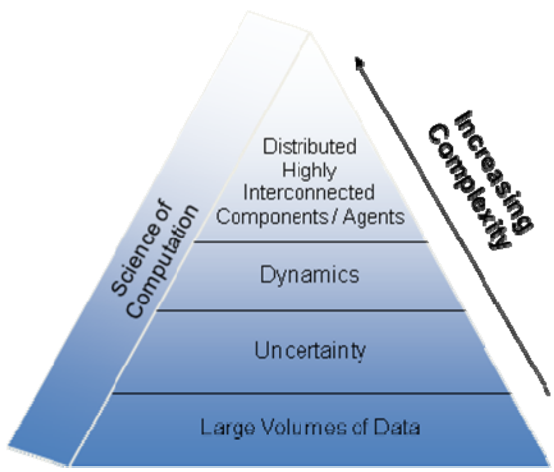

FIGURE 3 Increasing levels of complexity in computational sustainability problems.

SUMMARY

Computational Sustainability is a new interdisciplinary field that aims to apply techniques from computer science and related fields, such as information science, operations research, applied mathematics, and statistics, to help manage the balance between environmental, economic, and societal needs for a sustainable future. The focus of Computational Sustainability is on developing computational and mathematical models, methods, and tools for decision making and policy making concerning the management and allocation of resources for sustainable development.

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