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MODELING AGROECOSYSTEMS AS COMPLEX, ADAPTIVE SYSTEMS

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Abstract

Current challenges in modeling ecosystem structure and function based on multi-disciplinary concepts drawn from the study of complex adaptive systems are presented. To test alternate hypotheses related to these goals, different models are required and they can be differentiated by several main attributes: degree of determinism, degree of complexity, degree of discreteness versus continuity, degree of data-intensity versus sparseness and degree of linearity versus nonlinearity. Different approaches to representing and modeling ecosystems are showcased in three applications of research in progress: 1) Modeling greenhouse gas emissions to estimate potential bio-energy reductions and associated impacts on soil carbon and nitrogen, 2) spatially-explicit simulation of an agro-ecosystem model based on a high-resolution (daily, 10km) agro-climate grid for Canada, and 3) stochastic modeling to predict rates of de-nitrification and nitrous oxide production in freshwater and terrestrial ecosystems.

Keywords: Adaptive, complex, ecosystem

Introduction

Current challenges and insights

More land was converted to cropland in the 30 years since 1950 than in 150 years between 1700-1850 (DeFries et al. 2004). Roughly half of all global ‘useable’ land is already under pastoral and intensive agriculture requiring nitrogen and phosphorus inputs that surpass thresholds considered environmentally detrimental, and at rates likely to triple as food production doubles alongside population growth by 2050 (Tilman et al. 2002; Tilman 2001). Such intensification continues to increase the interconnection of local human activities and to strengthen the association of impacts across terrestrial, aquatic and atmospheric environments. High levels of nitrogen fertilization and agricultural losses accumulate in estuaries and coastal waters harming fish habitat and endangering fish survival due to eutrophication, over-enrichment and low-oxygen conditions. Harmful impacts are also caused by phosphorus loading in lakes, rivers and streams. Nitrogen fertilization also increases the emission of harmful greenhouse gases (i.e., nitrous oxide, methane, carbon dioxide) and atmospheric pollutants (e.g. nitrogen oxides) that then diffuse, transport and deposit inducing broader spatial and even time-lagged behaviour making it increasingly difficult to resolve a source or identify a main driver behind an impact (Schimel et al. 1997). These cumulative impacts emerge at a regional scale arise from multiple interactions of local scale activities, with a net-intensity that depends on their degree of temporal simultaneity and spatial scale.

Recent reviews of agricultural sustainability provide a synthesis of current knowledge and concepts relating improved land-use and nutrient-use to leading factors that affect use-efficiency. These studies reveal the great potential for furthering and applying concepts and principles drawn from the multidisciplinary field of ecosystem science. Such principles guide the exploration of multiple agricultural management objectives in an effort to meet broader, longer-term goals. Such a broader goal is to engineering agroecosystems to be more efficient and conserved nutrient and water-use, while reducing crop and livestock disease, controlling pests and reducing atmospheric emissions. Yet to achieve significant increases in nitrogen-use efficiency, knowledge of how best to integrate sustainable practices is required, because no one practice can *a priori* achieve target reductions. For instance, in addition to the practice of better timing and spatial application of nitrogen fertilizer to match plant/crop uptake, other practices are needed, that include multiple cropping, techniques of better handling and treatment of animal wastes, and agroforestry. It is therefore only collectively that such practices may achieve a sustainable, long-term balance in nutrient and water use by increasing nutrient availability and reducing gas emission losses.

Sustaining the current intensity of agricultural practices poses tremendous challenges for agricultural engineering. Likewise, unraveling direct and indirect human impacts on ecosystem health over the long-term poses unique challenges for agricultural science (Matson et al. 1997). And as human-driven ecosystem impacts continue to intensify, so too will the need to balance multiple, reversible and irreversible trade-offs in societal land-use, ecosystem inputs and production efficiency controls. From the science and engineering perspective, future decision-making will require improved methods to reliably estimate, predict and forecast sets of competing and inter-related factors that affect *economic* production efficiency, *ecological* cycling of carbon and nitrogen, environmental and atmospheric pollution alongside societal costs and benefits. To help integrate knowledge and insights across scientific disciplines in a cohesive, clear, the theoretically-sound and operationally-viable way, reliable analytical methods and models are critical. Only with reliable methods and actual tools capable of reliably testing established knowledge and newer ideas, can we begin to explicitly address different levels of uncertainty and learn how to better sustain the structure and functioning of agroecosystems over the long-term. With automated tools available, multi-disciplinary collaborators can work together in a practical and effective way to extend their knowledge while also relying on existing theoretical and experimental knowledge.

One of the most important areas for integrating theories and experimental techniques more broadly is that of uncertainty analysis because different levels of measurement uncertainty and model accuracy constrain and limit the applicability of success of strategic experiments as well as overall reliability in testing alternative hypotheses. One can ask alternative hypotheses and test them using integrated frameworks, but uncertainties must be quantified to resolve existing knowledge gaps concretely. Also, hypotheses often contain dual (or multiple) objectives making it difficult to test them or to identify how do they fill or bridge existing scientific knowledge gaps. Often the questions we ask are not even easily represented by nesting hypotheses, for example the following questions contain multiple objectives not easily testable, but are the same questions that human society demands answers to: “How to best maintain high agricultural yields under climatic disturbances, while minimizing nitrogen loss through groundwater flow or between terrestrial and aquatic habitat in agroecosystems?” Or alternatively, “How best do we assess cumulative impacts of non-point source and point-source environmental pollutants from agriculture that are harmful to both agroecosystems and human health?”

Ecosystem science perspective

Integrated, risk decision-making frameworks must consider off-farm demands for the sufficient, secure and equitable distribution of food, fibre, energy and material products and constraints and controls outside of the open boundaries of agroecosystems (Waltner-Toews 1996). Their applicability depends on highly innovative policy initiatives and use of adaptive mechanisms to help stabilize supply in local, regional and global markets, so as to enhance affordability and the adoption of beneficial environmental practices. Lackey identifies complexity, polarization, winners/losers, delayed consequences, decision distortion, national versus regional conflict and ambiguous role of science as the main qualities of ecological problems and policy decision-making (Lackey 2006). But existing disciplinary barriers limit policy innovation and potential for scientific creativity that arise from multi-disciplinary knowledge exchange. And such exchange is so crucial for developing and maintaining a coordinated systems-oriented framework to address environmental costs and footprints and to resolve agricultural productivity alongside environmental integrity (Antle et al. 2001; Robertson and Swinton 2005). As the value of market and non-market ecosystem goods and services increases, management and policy decisions must better organize multiple, competing uses and ensure that good and services are affordable. Decisions must weigh environmental and societal costs extremely carefully. While such frameworks may prove successful over the short-term when applied to isolated regions over isolated periods of time, agricultural science and engineering is still in its infancy in being able to successfully operationalize integrated frameworks across broader spatial and temporal scales. Moreover, education required for people to adopt and gain confidence in such frameworks will continue to challenge all stakeholders, in part because of an ever-increasing list of short and long-term costs and benefits as more knowledge is gained.

What weight do we give conserving biodiversity, in a riparian or wetland zone compared to reducing nitrous oxide greenhouse gas emissions from a crop zone? While such questions are fundamental to ecological theory and motivate scientific enquiry, they provide immense management and policy hurdles. Such hurdles exist in applying ecosystem science and engineering principles, because many of the questions ecosystem science asks are fundamentally complex. Even if we assign weights by unbiased estimation of long-term risks or short-term uncertainties, the ability of ecosystem dynamics to respond differently to combinations of disturbances remains a possibility – a question tantamount to separating the knowable unknown from the truly unknowable (Levin 2002). Ecosystems may undergo irreversible structural and functional changes, or may adapt in a reversible way – the potential for agroecosystems to change abruptly in an adaptive way is likely given all the variables at play. It is this adaptive potential that makes intensively managed ecosystems are more fragile and vulnerable to stress (Levin 1998; Levin 1999; Levin 2002; Levin et al. 1997). Changes to biodiversity by agricultural practices can cause differences in environmental sensitivity among functionally similar species helping to stabilize ecosystem processes, whereas differences in sensitivity among functionally different species make ecosystems more vulnerable to change (Chapin et al. 1997). The complexity or 'the cooperation, coalition, and networks of interaction that emerge from individual behaviours and feedbacks' within dynamic agroecosystems hinders our ability to predict and forecast likely outcomes of agricultural practices (Cadenasso et al. 2006). This is especially true as we move into a new realm of historically unprecedented global population expansion, climatic warming and agriculturally-driven environmental change.

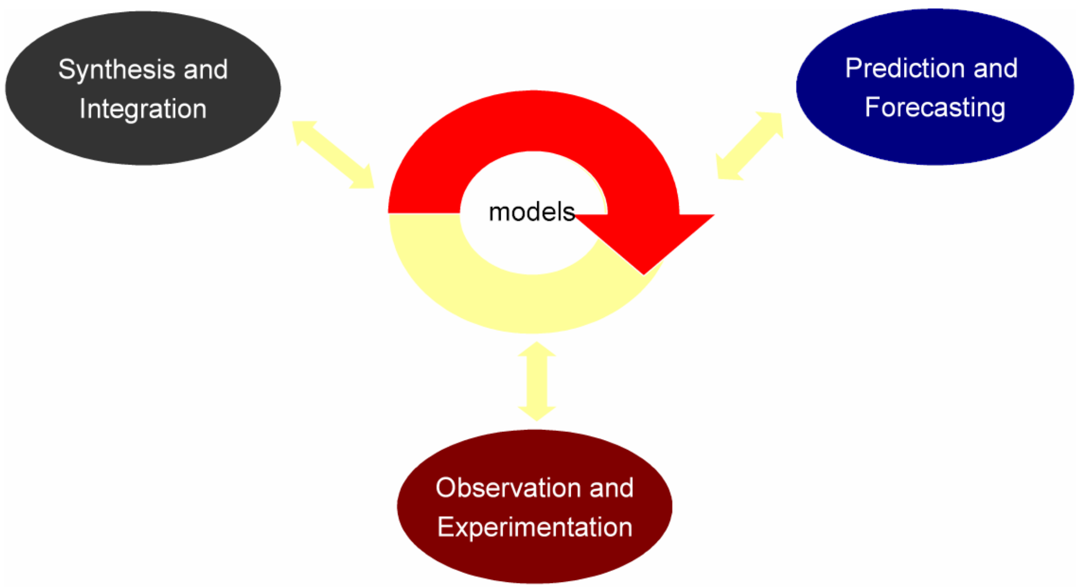

Figure 1. Modeling is a central step in scientific enquiry that tests alternative hypotheses and assumptions against observational/experimental data. Synthesis and integration of hypotheses, assumptions, data and models and theory (i.e., all levels of enquiry) are capable of providing a complete synthesis/integration of information that can be extrapolated to predictions and forecasts and then validated against new, independent data.

With a perspective of the current challenges in understanding agroecosystem structure and function and of multi-disciplinary ecosystem science, I discuss the applicability of complex adaptive systems theory to address such challenges in the context of the main attributes of existing ecosystem models. Following this discussion, three applications of CAS modeling approaches are presented. The aim of this paper is to present a brief introduction to modeling agroecosystems as complex adaptive systems and to encourage greater multidisciplinary collaboration, development and testing of CAS models by agricultural scientists and engineers.

Complex, adaptive systems

When adaptation is included in systems behaviour, complexity arises. As one cannot describe, measure or model all variables in a complex system at once, complex, adaptive theory describes how theoretical insights and data from small-scale experiments may be combined to better understand and predict large-scale patterns and processes. This theory offers a powerful framework for studying large, interacting systems: 1) where patterns are not simply related to the sum of individual behaviour of distinguishable components, 2) where the dynamical behaviour of a system is operating far from equilibrium conditions and 3) where system processes are strongly, interacting and/or highly dependent upon each other. Figure 2 provides an overview of the interconnection between observable pattern/s and underlying processes in a CAS system and models that describe them.

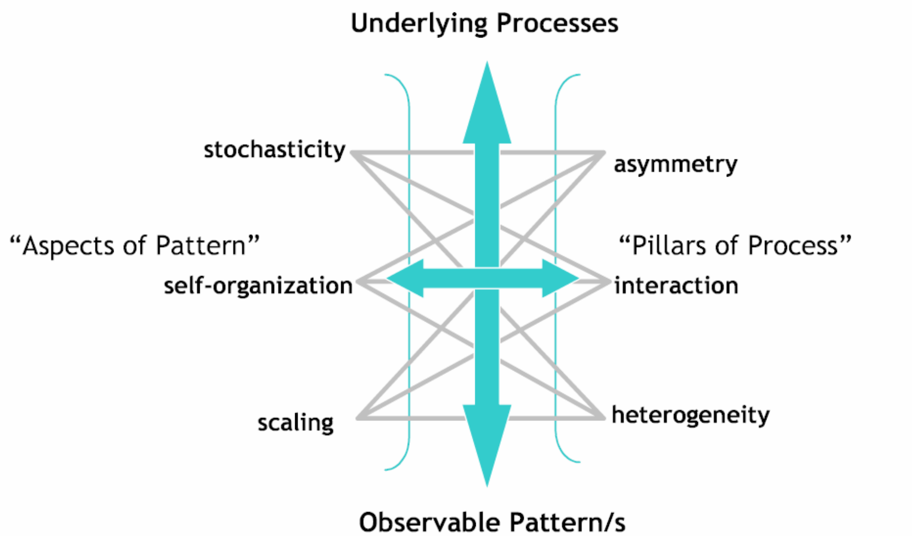

Figure 2. Schematic overview of the interconnection between observable pattern/s and underlying processes in a CAS system and models that describe them. Asymmetry, interaction and heterogeneity of interacting ‘agents’, ‘units’, or ‘objects’ can be measured thereby elucidating ‘pillars of process’: asymmetry/diversity in behaviour, strength of interaction and spatial arrangement responsible for generating observable system-level pattern/s. Likewise, stochasticity or randomness, self-organization and scaling properties that are measurable as processes interact together generate ‘aspects of pattern’. With observable patterns revealing hidden processes and observable processes revealing hidden patterns, complexity of a web of interconnections between an ecosystem’s structure and functioning can be explored

A complex system can be defined as ‘a system that exhibits emergent properties from small-scale interactions’. Modeling of complex adaptive systems (CAS) has shown how local adaptation has profound consequences for global, system-level outcomes, with behaviour described as ‘emergence’, ‘self-organization’, ‘criticality’ and/or ‘extended memory’. CAS theory and models also enable an integration of physical, biological, chemical and ecological theories and data offering new approaches to test existing theories that previously were considered intractable or could previously only be approximated. Perhaps, the main thrust behind CAS theory has been the wide availability of computers and their numerical power. Computational power now enables both deterministic or mechanistic models to be numerically simulated, as well as statistical approaches that model uncertainty and higher-order effects that were excluded by previous analytical/numerical approximation (Cottingham et al. 2003; Levin et al. 1997; Wang 2005). The extent that modeling and experimental data collection, analysis and integration has progressed in the fisheries science, for example, is revealed in changes in management and policy, even though integrative assessment to match management goals can often lags behind due to complexity. For example, fishery science now explores migratory marine fish populations to comprise not only individual fish of different ages/weights/lengths, but as spatially-discrete populations with different survival and adaptive behaviors with individuals interacting over an oceanscape. Essential properties of CAS models are: diversity (asymmetry), interaction, nonlinearity and aggregation. These models explore questions such as: What characteristic patterns are generated by a system? Are the patterns uniquely matched to changes in local conditions? How do ecosystem properties change? How does system structure change? What relationships exist between system structure and its functioning? How do we define and measure sustainability, resilience and criticality of a system? (Bar-Yam 1997; Cadenasso et al. 2006; Hartvigsen et al. 1998; Levin 1998).

To build a CAS model there three main divisions of steps involved. They are: 1) multi-disciplinary, 2) collaborative and 3) community-wide. Individual steps within each division are outlined below with terms that refer or specify each step also provided in brackets:

Multi-disciplinary

- Define what model is trying to explain or test (alternate hypotheses)
- Define the object/agent (chemical, physical, biological, mixed)
- Select a space-time scale (reference)
- Identify agent properties, preserving diversity (symmetry, asymmetry)
- Identify what detail can be pre-determined, what cannot (reducible, irreducible)
- Define rules of agent interaction (direct, indirect)
- Define autonomous process whereby agents adapt (random, mutation, mixed)

Collaboration between modellers-experimentalists

- Simulate in time - look for emergent order, patterns (simulation)
- Examine processes: test degree of system irreversibility, predictability (sensitivity)
- Define measure of goodness, agent fitness (optimization)
- Test model to independent data (validation)

Community-wide collaboration

- Compare between models – assumption bias and uncertainty
- Apply model to different data-sets – model bias and uncertainty
- Robustness, reliability, application to wide variety of conditions?

In applying CAS models to test alternate hypotheses, different structures or approaches are often necessary and their engineering design can be differentiated according to some of the main attributes provided below. The engineering of CAS models to address a given problem really depends on the scientific information available to construct, verify and validate a model. Note that the list below is not meant as a complete set of all possible model attributes or all possible independent assumptions.

Model Attribute	**Alternative assumptions**	
Predictability	Deterministic	Stochastic
Complexity	Fixed	Variable parameters
Scalability	Linear	Nonlinear
Divisibility	Discrete	Continuous
Uncertainty	Reliance on data	Reliance on model reliability

Following my brief overview of CAS modeling and providing steps that agricultural scientists and engineers can use to design and apply CAS models, I outline three different approaches.

Network CAS modeling

A network model structure is constructed by distinguishing separable components either according to existing correlation strengths of observable variables from data or by assumption where one can assume two components are separable and then put a resulting network structure to the test. Separable components can be distinguished according to a single or set of variables that may be further assumed to be fixed or to fluctuate. Depending on how state variables are defined, components become more independent in a deterministic or statistical way according to the correlation or cross-correlations between state-variables. Once components in a network structure have been identified, then one proceeds by identifying linkages or flows between them. Perhaps the main distinguishing feature of CAS network models from other network models is that they include assumptions on how state-variables or flow-variables adapt. The assumptions of a model often determine the appropriate mathematical framework for specifying equations or relationships. Such relationships/equations may be represented as differential or discrete, for example, depending on whether space and time is considered a continuous or discrete variable. A network CAS approach is currently being used to model farm-scale greenhouse gas emissions. Here, diversity/asymmetry is represented between component storage, flow and feedback interactions of carbon and nitrogen. Nonlinearity is represented in component storage, and in response of flow to temperature and precipitation. Self-organization occurs as individual components interact and adapt from initial conditions and as the system proceeds far from equilibrium (i.e., mass-balance conditions) various system-level properties that emerge can be explored. Complexity increases as the number of interacting components increases. By specifying nonlinear equations for emission losses driven by carbon and nitrogen flow through a system, patterns of net-emission of greenhouse gases (GHG's) (i.e., carbon dioxide, nitrous oxide, methane) can be profiled. Such profiles represent cumulative emission losses over time and aggregate carbon and nitrogen flow. This approach is best applied when one wishes to test hypotheses relating to temporal aspects of pattern or behaviour of processes at a fixed spatial scale, whereby spatial details and dependencies are assumed fixed or neglected. Currently a network CAS model of Canadian agroecosystem emission losses is being developed and tested by a multi-disciplinary collaboration of scientists (Janzen et al. 2006; Newlands et al. 2006) to examine net-GHG emission profiles at the farm-scale.

Spatially-explicit CAS modeling

Spatially explicit, high-resolution meteorological data are becoming increasing important as inputs to ecosystem and regional scale models in agriculture and forestry. This new information provides climate variation input into ecosystem models: crop growth, development and productivity, soil erosion, drought and GHG emissions of agroecosystems. With realistic variation, we can better understand the impacts of extreme events and conditions (i.e., water, soil and air quality) and identify the best ways to guard against potentially harmful impacts. Unlike the network approach, spatially-explicit models are used to describe spatially-dependent features that network CAS models often neglect. Interacting components are spatially-referenced, with their interactions spatially-correlated. Components and other distinguishable agents are allowed to interact with each other and with their local or nonlocal environment. In this way, even though a complex system may have no clear boundaries, environmental variables are considered in a CAS model either by perturbing a model's spatial and temporal boundaries conditions, or in perturbing states and flows in a nonlinear way. Aggregation in these models is generated by emergent, sink-source dynamics observable at different thresholds of spatial correlation. Often the patterns that emerge from these models depend on the degree of diversity in component characteristics and how heterogeneous their adaptive interactions are. A high-resolution computational grid for ecosystem modeling is useful for simulating spatially-explicit

CAS models over small time-steps. A computational grid enables estimation of the probabilistic likelihoods of different output patterns or scenarios a spatially-explicit CAS model generates. Also, computational grids coupled to CAS models enable the exploration of system response to a range of simulated disturbances. The reliability of such simulation findings depends on model and data uncertainties, so drawing direct inferences is often difficult. A formal uncertainty analysis can then be used to generate predictions and forecasts with a varying degree of confidence. Coupling a spatial CAS model to a computation grid enables one to explore a broad set of outcomes, many of which may never have been observed. This approach is also useful in delineating spatial regions where small-scale experimentation can test a CAS network model.

Stochastic CAS modeling

A stochastic CAS model structure enables representation of a complex suite of controls on a process or set of processes. These models may be nested within a larger network CAS structure or can be used to extract dynamics of a given system component for more detailed representation, exploration and testing to data. When coupled with a spatially-explicit CAS model, stochastic CAS models can be used to test alternative hypotheses involving spatial diffusion, transport and deposition resulting in patterns and morphologies of transport pathways. For instance, In the case of nitrification and denitrification processes in agricultural terrestrial or freshwater systems (i.e., streams, rivers, lakes), ammonium [NH4+], oxygen, phosphorus, acidity, temperature, and soil moisture enact different control over nitrification, and nitrate [NO3-], oxygen, sediment contact, flow rate and residence times of nutrients controls denitrification. Here, a stochastic CAS model that can consider all these variables at once may lead to a better understanding of the controls on de-nitrification and nitrous oxide production in agroecosystems. This is because such these models mathematically describe stochastically-controlled switching to mimic adaptive behaviour between microbial agents. A stochastic CAS model may also provide useful insights on understanding spatially-heterogeneous patterns of nitrous oxide emission from agroecosystems, whereby model output can be statistically compared to observed hot-spots/hot-moments of microbial-mediated nitrogen transformation.

Final thoughts

This paper introduced complex, adaptive systems theory and outlined steps for building CAS models. How this approach aids system science and engineering was described in the context of current challenges in modeling agroecosystem structure and function. From the perspective of ecosystem science, the incorporation of CAS theory requires a multi-disciplinary approach to addressing problems and relies on bridging concepts, theory and data across traditionally-organized disciplines. Ecological problems also require integrated hypothesis testing and ecosystem modeling enables exploration of the probability of system outcomes. Applying CAS theory and constructing network, spatially-explicit and stochastic CAS models to represent and test adaptation of ecosystem structure and interacting processes, offers a way to not only explore the probability of system outcomes, but also their likelihood.

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