CHAPTER 4

MICHAEL HAUHS* AND HOLGER LANGE**

FOUNDATIONS FOR THE SIMULATION OF ECOSYSTEMS

INTRODUCTION

Interactive simulation of ecosystems is a new computational technique that extends the scope of information technology (IT) applications into ecology. As with every newly introduced technology, it has the potential of changing the problem perception within its field of application. What appears now as a technically solvable problem, and what remains an unsolvable problem – technically or in principle? By their successes and failures, simulation models may change the attitudes toward ecosystems not only in science but also in ecosystem management. The relationship between ecosystem practice and research is usually a problematic one (Peters 1991; Beven 2001; Bocking 2004; Kimmins et al. 2005). Successful utilization schemes predate ecology and ecosystem research, as can be seen, for example, in the "plenterforests" of Central Europe (Schütz 2001).

Ecosystems commonly fall under the rubric of complex systems (West and Brown 2004). Nevertheless, in the practical management of certain ecosystems, we encounter simple heuristic rules of human interference that are often derived from cultural traditions rather than from scientific study. The increased technical power of computer-based simulation tools and their increased mathematical formalization may either remove former technical limits (e.g., of prediction) or, in contrast, reveal the fundamental character of some of these limits. Here, we shall argue that both cases occur, and that the main effect of simulation technology is to bring the distinction between these cases into scientific awareness.

This chapter is organized as follows: First, we clarify our terminology to demonstrate that we are actually introducing a new modeling paradigm, and exemplify its domain of application. Then, we briefly review the traditional algorithmic modeling paradigm for state-based systems before discussing interactive simulation as an extension to this based on the mathematical notion of streams as an abstraction of behavior. We try to show that interactive simulation becomes especially useful when applied to models of living systems and ecosystems. Finally, we discuss the different limits encountered in genuine interactive behavior and displayed by genuine complex systems. Although both notions can be used to address theoretical and practical limits

J. Lenhard, G. Küppers, and T. Shinn (eds.), Simulation: Pragmatic Construction of Reality, 57–77.

of simulating ecosystems, currently, complexity is used exclusively for demarcating limits of simulation models (Ulanowicz 2004). Interactive simulations may explain the empirical simplicity that is often encountered in ecosystem management. Thus, they ought to play an enhanced or even dominating role in theoretical as well as applied ecosystem research.

INTRODUCING TERMINOLOGY

For systems as well as models, we distinguish between algorithmic and interactive types of *behavior*. Behavior addresses all kinds of temporal changes, both in an active and a passive sense. In particular, we use a notion of behavior that goes beyond dynamic systems theory and allows for active *choice-making* behavior within the systems considered. In dynamic systems theory, behavior is reduced to (algorithmic) functions of *state transitions* alone. The concept of state is a very prominent modeling abstraction developed in physics.[1] However, active choice-making behavior is impossible to incorporate in algorithmic models, although it is often encountered in living systems.

The Traditional Algorithmic Modeling Paradigm

In algorithmic models, functional behavior is reduced to structure, that is, the configuration of objects in (state) space and their change over time under the entailment of 'Natural Law' (Rosen 1991). The observed behavior in, for example, experiments can be *explained* or predicted algorithmically by a system of equations subject to specific boundary conditions. When one views the world from this approach, behavior is inevitably reduced to a secondary role, referring to state transitions governed by dynamics. Many examples of this approach and the relationships between structure and function are given in the introduction to this book.

In the cases of ecosystems and social systems, the observed structure appears to be irreducibly complex. Thus, any simplicity or regular behavior encountered in these systems appears surprising to 'reductionist science' and is typically lost in scientifically rigorous approaches to such systems. Ecosystem researchers confronted with some seemingly simple rules of ecosystem managers tend to ascribe their success to a system simplification obtained by taming; the main effect of, for example, agroforest monocultures is a reduced number of degrees of freedom (Bocking 2004). On the other hand, the predictive ability of models based on scientific process understanding (e.g., for a forest under climate change) is very low. This mismatch is a hint that the wrong modeling paradigm might be being used.

Where these systems are studied and simulated today in ecosystem research, the ultimate goal is to replace the heuristics of management with a process-based understanding of the dynamics (Lansing et al. 1998). Here, scientific knowledge in considered to be, in principle, superior to any other form of knowledge. The leading example in environmental and ecological sciences is meteorology, in which empirical models have been replaced successfully by physical models in operational weather prediction. The computational tools used for weather prediction express the current technical limit of the state model type introduced by Newton. Its solution was already recognized as a technical problem a century ago (Bjerkenes 1904). Attempts to sketch a similar path for the simulation of ecosystems (including the complete biosphere) appear much less convincing (Schellnhuber and Wenzel 1998), because they lack thorough real-world case studies. The application to climate models already has to deviate from a mechanistic recipe of dynamic state theory (see Lenhard's argument, this volume, and the introduction).

The Interactive Modeling Paradigm

Systems with relatively simple external behavior at a user interface and complex internal structure occur today in high-end human technology. A computer is only one out of many examples for designed systems that, while becoming increasingly difficult to built, are simpler and more robust to use. A computer is deliberately designed to provide a simple intuitive service. Recently, a number of theoretical approaches have been suggested to express formally 'what computer scientists do' when they build interactive or concurrent programs. These approaches are based on the notion of streams and are, mathematically speaking, algebraic duals to the traditional, algorithmic ones in computer science (Gumm 2003; Arbab 2005). Instead of seeking the model that provides the simplest explanation of a phenomenon by identifying an initial state, they search for the most comprehensive model of behavior in terms of sets of streams.

Examples for interactive behavior include cases in which the simulation is not derived from a comprehensive scientific understanding or reconstruction of the modeled ecosystem, but documents and communicates heuristic knowledge about (managed) ecosystems and how they have been actively sustained by human interference.[2] We shall argue below that such simulations have been established in other areas and may, in a more long-term perspective, change the foundations of ecological modeling.

Applications of interactive simulation models occur in many fields today. Prominent and well-established examples are chess computers or flight simulators. We shall argue that silviculture in forestry may provide examples of interactive simulation as well, and that this model type may be regarded as a fundamental one in terms of ecosystem research. We conjecture that interactive simulation models are qualitatively different from the model classes used in physics.

This chapter takes an 'engineering perspective' on interactive behavior: The (supposed) simplicity of ecosystem responses as perceived in traditions of, for example, hunting, farming, or silviculture provides us with a unique modeling challenge. There may be considerable human expertise (skill) present in any of these traditions, but skill[3] when evaluating and deciding on proper management is difficult to explain within a scientific context. Skilled behavior toward ecosystems can be referred to as 'tacit knowledge.' In traditional indigenous utilization schemes, it is part of an embedded relation with respect to the environment. It may appear in sharp contrast to scientific attitudes toward and perception of the same environment (Ingold 2000).

Where traditional systems of ecosystem management and land use have been studied in anthropology, the leading paradigm of the natural sciences has been criticized, and an extension to it has been proposed (Ingold 2000). We shall show below that the technical and theoretical extensions provided by computer science to the issues of interactive computation in the form of modern simulation models correspond to the concepts derived in anthropology to classify human culture: They all seem to aim at the (irreducible?) interactive aspects of these systems. It can be conjectured that earlier attempts by 'western' scientists to substitute indigenous forms of land use knowledge by dynamical models might have failed for principal reasons when truly interactive situations were involved. How much interactivity is implicated in a given ecosystem management scheme varies a lot and needs empirical testing. With the modern extension to IT, however, these situations can now be studied much more explicitly and locally. Silviculture in forestry serves as an example here.

When searching for the most appropriate simulation model class (algorithmic or interactive), we answer three parallel questions in the context of modeling the *behavior* of ecosystems:

- What is it that humans do, when they manage an ecosystem to fulfil a function[4] (and make a living)?
- What is it that scientists do when they study and model an ecosystem (to understand it, document and narrate its past; or estimate its future, evaluate its potential)?
- What is it that a computer provides, when modelers try to represent knowledge (managerial and scientific) and simulate an ecosystem?

We start with the definition of interaction proposed in computer science that provides us with a precise and sufficiently general notion of (choice) behavior in machines. The functional (algorithmic) behavior of machines will subsequently be recovered by imposing restrictions (i.e., algorithmic models are a special [limiting] case of interactive ones). An interactive model contains two elements:

- *streams* (Gumm 2003) serving as the mathematical representation of behavior, for example, of choice events that characterize an ongoing or already realized interaction, and
- a *real-world context* in which the outcome of any choice depends upon the sequence of choices made before. The outcomes of realized choices and the choices still to be made in the future are related through valuation and norms – technically, these introduce equivalence classes in the set of possible choices.

Typically, normative constraints will apply to choices. Take the following three examples:

- In chess playing, the options of winning should not be decreased as a consequence of the current choice.
- In airplanes, the options for a safe landing should not be decreased by an actual maneuver.
- In sustainable forestry, the options for further production and productivity should not be decreased by an actual thinning or harvesting decision.

In all three cases, the normative element stems from a predefined goal function (to win, to land safely, to sustain timber production). However, in computer science, a typical situation even lacks goal orientation, as in a persistent client/server interaction in which perennial service provision on the server side is mandatory but not an element of the 'goal' of the interaction with the client. It is obvious that the 'ultimate' outcome (after any finite time) of an ordered 'stream' of choices is fundamentally unpredictable for an algorithmic model. By definition, a precisely predictable situation[5] is noninteractive, and could only be considered as such by an observer ignorant of this algorithmic possibility. In any other situation, the choices taken become interspersed with evaluations of their outcomes and a reassessment of the altered potential for follow-up choices. This is one of the most important aspects by which the algorithmic and the interactive simulation models differ. In an algorithmic simulation, the predictive task is the challenging one, whereas evaluation of its results is relatively easy (again, weather prediction provides an illustrative example). In an interactive simulation, the evaluation task is the challenging one, whereas the (immediate) prediction of the results of the next choice is trivial, and the long-term prediction either appears to be or is impossible. Here, chess playing, silviculture, and pilot training share an interactive character demonstrating the need for a new abstraction in simulation models.

The reason for this difference lies in the relationship to the environment and not in the system itself. The options provided by the environment through an interactive interface may change as a result of past choices, and an observer *enclosed* by interactive interfaces meets an algorithmically unsolvable problem. For example, in plantation forestry, more trees are planted than will ever reach mature age. However, at the time of planting, which trees are to be harvested or taken out is left open for later thinning decisions. Here, the reason is the phenotypic plasticity of trees, or the genotype/phenotype distinction in general. Uncertainty with respect to the actual soil conditions (may vary due to spatial heterogeneity) or with respect to the actual weather conditions over a rotation period renders interactive decisions by foresters in many cases inevitable.

In flying, the interaction between different airplanes or with traffic control leads to another example in which choice situations posed by the environment are unpredictable but can be handled more efficiently through interaction. These choices require the proper training of human pilots in (interactive) flight simulators to reliably provide the necessary competence.

GENERALIZING NOTIONS OF BEHAVIOR: WHAT IS INTERACTION IN COMPUTER SCIENCE?

Models for computation are usually based on the notion of the Universal Turing Machine (TM). Recently, an extension of the TM to a *Persistent* Turing Machine (PTM) has been proposed by Goldin et al. (2004) and Wegner and Goldin (1999). Persistence is introduced by a read/write tape that is *not* reset to an initial state between subsequent computational cycles. The PTM interacts with its environment in the sense that later input from the environment may depend upon former output from completed computations of the machine. PTMs may imply a new and more general meaning for 'computing' than the TM. If we want to restrict the notion of computing to what is formalized by TMs, than it becomes unclear what extra services today's computers are able to provide (Arbab 2005).

This relationship between external interactive behavior and internal persistent memory states also holds outside computer science. It links memory and a privileged perspective from the inside with interaction on the outside. We apply it here to explain the pattern encountered in the success and failure of ecosystem modeling and simulation. What new capacities and limits of *interactive* computing can be expected to be relevant for describing and abstracting those real-world systems that have resisted progress in algorithmic computing so far? Whereas in the algorithmic model, one needs to distinguish computable from noncomputable functions, the limits of interactive models exist between unbounded and bounded forms of interaction depending on the question whether entirely new features and choices may appear at any time. Candidates for unbounded interactions are open-ended evolution (life) and open-ended communication (culture). In the realm of interactions, the cases in which the class of all possible choices has a finite (infinite) representation are termed bounded (unbounded). We see little or no progress in the capacity to predict ecosystems as computers become faster and able to handle observations from more complex systems (see Figure 1, upper part).

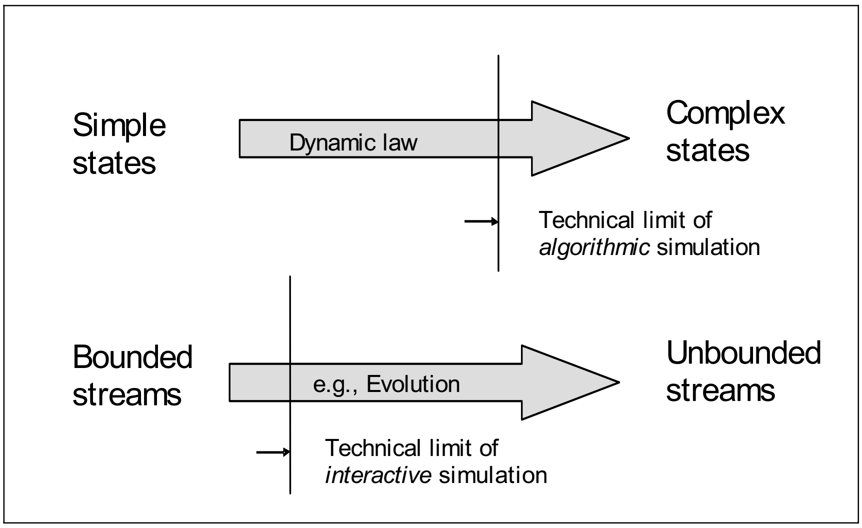

Figure 1. For algorithmic simulation models, a state may be too complex to be represented by a computable function (as e.g., in chaotic systems). For interactive models, the set of choices that produce entries in a (data) stream may be bounded or unbounded (as, e.g., in biological or cultural evolution). Only bounded sets can be represented in any model of an interaction

However, we may still expect progress when, for example, the relationships between forest growth models and a forester become represented by interactive models, and formerly unbounded situations can now be evaluated as bounded ones. All three examples above match this situation, whereas in chess, a winning strategy has remained algorithmically unattainable, the online access to the documented history of played out matches allows interactive simulation models to treat the choice problem as (almost) bounded (see Figure 1, lower part). In pilot training, flight simulators become better; the critical situations that may occur unexpectedly have become documented and are covered by the simulator. In silviculture, only the very initial steps in this direction have been taken, but, here as well, a bounded choice situation based on the historically documented and approved examples has become technically possible (Hauhs et al. 2003).

GENERALISING TERMINOLOGY: MODELING, COMPUTATION AND SIMULATION

We shall use the terms modeling, computation, and simulation in the following sense. *Modeling* is the most general activity, referring to a symbolic or virtual aspect of an investigated system in relation to its observed structure and/or memorized behavior.[6] Modeling is based on (consists of) mappings, termed 'representation' and 'implementation,' that establish relationships between a real, concrete realm of the world we live in and an abstract or virtual world providing the (partial) referents for models (see Figures 2 and 3). Social systems individually and collectively have access to the real world through observation and memory. They have established procedures (partly outside science) on how agreement can be achieved between different

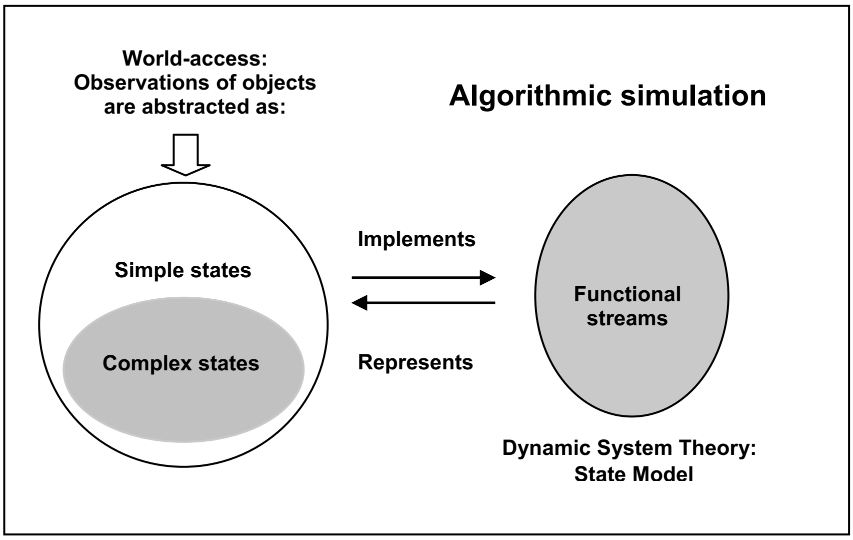

Figure 2. Relationships in scientific modeling (under the state model paradigm). In the real world, every system has a set of observables attached, which are represented as abstract state variables. Time variations in states are conceptualized as abstract functional *behaviors resulting from transitions under a dynamic law. Experiments in the real world can be conceptualized as local implementations of the dynamic laws. This traditional modeling paradigm will be referred to in the text as 'algorithmic computation.' A model in which the functional behavior is inferred from a 'faithful' representation of the observed states is termed an (algorithmic) 'computation.' A model in which the functional behavior is inferred without restrictions about the states is termed here an (algorithmic) 'simulation'*

individuals and subgroups over the content of their observations and memories. In a scientific context, access by (objective) observation is regarded as superior to access by memories (Rubin 1995; see Figure 2).

Modeling as a science needs to be open to testing, criticism, and revision. Scientific models are distinguished from nonscientific models by this grounding procedure in empirical knowledge agreed upon among a group of experts and open to critique. If, in addition, modeling can be a) formalized by mathematical structures or b) transferred into a (representational/symbolic) form in which steps are executed automatically by a computer, we will term this *computation.*[7] The sciences in which modeling can make use of an established (mathematical, systematic) theory are those that have developed *computational* branches, such as computational physics, computational chemistry, computational biology, or computational meteorology (the latter is not a standard technical term; we refer to computer-based weather forecasting as done routinely nowadays).

Other sciences, mostly those lacking underlying fundamental mathematical theories, use the label ‘modeling’ instead, as in, for example, ecological or environmental sciences. Besides scientifically based understanding, other forms of knowledge exist and are referred to as heuristics, skills, or tacit knowledge. Such forms of knowledge abound in ecosystem utilization and their respective management traditions (such as in hunting, agriculture, forestry, fisheries, gardening, etc.).

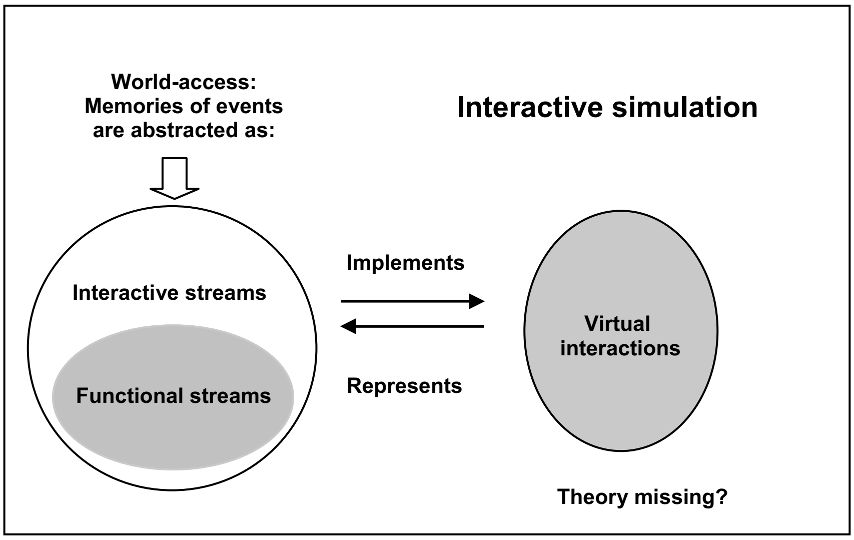

Figure 3. Relationships under the proposed second model paradigm. In the real-world system, time-ordered data streams are accessible by memory of agents. If the streams are generated interactively, they become represented as virtual choices in an interactive simulation (technically by persistent states of the interactive machine). Experienced time is conceptualized as choices realized by interacting partners subject to internal motives and social norms. This new modeling paradigm will be referred to in the text under ‘interactive model.’ It corresponds to a second and new notion of simulation, here referred to as interactive simulation

When the objective of the modeling is not to provide a realistic representation of the system's structure, but still to reproduce the observed behavior of target variables, the system is said to be simulated. In this usage, simulation means something different and, in terms of scientific rigor, *less* than computation. There is, however, a second use of the term *simulation*, and both of these usages have historic examples (see Terry Shinn's chapter in this book). The second case applies to situations related to interactive choices in which a body of knowledge changes only slowly relative to the lifetime of an expert. Relevant situations in which such tacit knowledge becomes relevant are sparse, and thus training to expert levels is a difficult task. Historical examples are generals' skills in battle tactics simulated in sandbox scenarios, or air force pilots' and gunners' skills in World War II simulated in analogue models of airplanes. Competence in chess playing simulated by modern computers can serve as another example or, as we shall argue below, many examples in ecosystem utilization such as silvicultural skills in forestry.

In this second sense, an (interactive) simulation approach represents *more* than a computational model (Figure 3). Despite the fact that the examples above appear to be modeled less rigorously when viewed in terms of the traditional approach, interactive simulations are practically without any rivals. In fact, they have added something new to the respective application field that is not yet properly accounted for in the foundations of modeling based on dynamic systems theory.

DEFINITION OF LIFE AND ECOSYSTEMS

Life is a phenomenon occurring at scales between macromolecules and the biosphere. Neither the molecular building blocks of a cell nor the global cycles of life's resources (e.g., of water) are alive. Physical processes can be used to delineate living systems from larger spatial scales by (noninteractive) functional behavior downward and from its simple (noninteractive) building units upward.

First. we shall try to define life and ecosystems exclusively using the terminology of the algorithmic model (dynamic systems theory). This represents an approach to define and relate terms by using established physical notions (i.e., reductionism). In this perspective, life is regarded as a phenomenon requiring a minimal complexity in order to execute or perform typical behavioral features such as self-reproduction, the abilities to adapt, evolve, and so forth. In this context, the potentially interactive character of these behaviors is (implicitly) abstracted away, or simply placed into the eyes of the observer. Above the complexity threshold and when provided with the appropriate conditions, the emergence of life may then become inevitable. Molecular biology seeks to identify minimal forms of living entities, whereas systems biology is often viewed as an attempt to compute or synthesize according to this modeling paradigm. These attempts have not been successful yet; in other words, the first living organism synthesized in the lab from molecular building blocks has still to arrive ("we are missing something fundamental" [Brooks 2001]).

At the other end of the scale, ecosystems are open to their environment and contain life. They do not live themselves but consist of living entities and abiotic constituents. *Ecosystem* is probably the most popular term among ecologists. It is defined only vaguely and carries many different meanings (even if we restrict its use to ecology alone). The openness toward its external environment can be described in (noninteractive) physical terms, for the living aspects we shall use interactive behavior as described in ecology. Thus, external boundaries delineating an ecosystem will be based on physical aspects, whereas delineation of behavioral epochs will be based on biological aspects.

Here we regard minimal ecosystems as the smallest evolvable living units that exchange abiotic fluxes of matter and energy with the environment in a noninteractive manner. When living systems become aggregated in the form of whole landscape units (such as watersheds), their behavior at the boundaries often becomes relatively simple and can be simulated algorithmically; matter and energy fluxes across watershed boundaries are functional (i.e., noninteractive). External relationships of such functional units can be studied only on the basis of the *physical* concept of interaction (*Wechselwirkung* in German).

In our terminology, an ecosystem is a noninteractive unit of a landscape (Pittroff and Pedersen 2005). The observed behavior of such units, however, appears as an anomaly in terms of hydrological transport models. It has not been possible to explain (uniquely reconstruct) runoff data by physical models (i.e., distributed hydrological models). Algorithmic simulation models are typically overparameterized with respect to the observed runoff data. The 'true' internal transport mechanisms needed to perform typical transport models cannot be identified directly from data. Within the algorithmic modeling approach, these difficulties are discussed in terms of the broad heterogeneity of hydrological catchments and the technical limitations of proper sampling.

To summarize, at the lower and upper cutoff scale of life, the modeling approaches based on algorithmic (simulation) models have, to our knowledge, not yet led to a 'living reconstruction' or a nontrivial prediction. There is a widely accepted explanation of these difficulties: Living entities and ecosystems appear to be (too) complex. However, empirical modeling of a runoff signal hardly involves more than two or three parameters (Jakeman and Hornberger 1993). This appears as an anomaly for algorithmic simulation models. Why does the complex system provide us with simple responses that turn out to be of particular interest for human utilization? We shall turn to the second modeling paradigm (interactive models) to seek more consistent answers to these questions.

We have suggested considering life as an irreducible interactive phenomenon. In order to extend this proposal to the ecosystem scale, we have to generalize the primitives used in the above ecosystem definition: Fluxes across the boundary will be generalized to streams.

STREAMS AND FLUXES

The basic mathematical notion used here for describing the boundaries of an ecosystem with an abiotic environment is a (data) *stream*.[8] A stream is a potentially infinite ordered (time) series of instances of discrete events – in our case, we are interested in abiotic events at the boundary of an ecosystem. With this application in mind, streams consist of transport events of extensive variables (matter, energy). Our primary example is water transport. Hence, we are seeking boundaries that are related to precipitation and runoff. These data streams can be described in a continuous or a discrete way; the latter being the canonical choice for digital computers. Also, measurements that have to respect the finite sensitivity of the instruments are inevitably discrete. The typical dimension will be that of a flux across a boundary, that is, mass per time and area.

It looks as if this is only a change of wording, because streams appear to be closely related to the flux concept. However, this terminology is implicated in the direction of evaluation. In hydrology, the relationships governing the input and output of water for catchments are usually described in terms of matter and energy *fluxes* that can be observed, and the theoretical framework taken from physics relates them to potentials and forces (gradients of potentials) that are not directly observable, but represent the states of the system. These relations are formulated as conservation laws, with mass budgets as the paradigmatic example. Local transport equations are obtained (such as Darcy's Law or Fick's Law) from the conservation laws using variational calculus. It is important, however, that the concept of flux as observed and transport as modeled quantity are formally independent if conservation is not given, as is often the case in nonequilibrium situations (e.g., for rainfall, sedimentation, or chemical weathering).

Streams are a more straightforward abstraction starting from the observed input and output of the ecosystem. Their definition refers to the temporal order among the recorded events and the fact that events can only be produced in an 'online manner,' analogue to that of infinite data types in computation (Gumm 2003). They imply an irreducible diachronic aspect and are therefore retrieved from the memory of an observer rather than being just (synchronic) observations of a state. In the algorithmic approach (Figure 1), states are accessible through observation and imply behavior (here fluxes) by their changes. Therefore, fluxes, when abstracted as a form of behavior, are derived from state changes. This relation becomes reversed under the notion of streams. Documented streams as memorized from past behavior (say a runoff record) imply corresponding internal states (mostly inaccessible to observation). Hence, in this perspective, the states are derived and evaluated from the memorized streams. As long as the stream is noninteractive, the difference between the two approaches is one of perspective only.

The usual conception of fluxes and forces is that they have a deeply rooted translational invariance in time built into them. This is of utmost importance both theoretically as well as culturally in physics: Nonrepeatable experiments and thus nonreproducible results are inacceptable and ignored in the scientific community. We propose that this worldview is impossible for ecosystems. History dependence and the implied uniqueness of each such system are crucial. Unlike observations from purely state-based, memoryless systems that can be reproduced, lost records about streams cannot be substituted in principle. This is reflected by the high value of long-term records in some of the environmental (hydrology) and most of the ecological sciences (Kratz et al. 2003). These facts make the abstraction as streams the more 'natural' for runoff from ecosystems.

We regard the definition and delineation of ecosystems based on the notion of streams as also being the more fundamental one. It allows us to address and to deal with simplicities in ecosystem behavior much more straightforwardly, rather than obscure such simple aspects by using elements of complexity theory from the beginning. Simplicity and universal features in runoff data may, in this view, be regarded as *signatures of internal interaction*. There is by definition no interaction in abiotic streams across ecosystem boundaries. The simplicity of runoff data lies in the fact that choices may produce simple patterns *after* they are made, but that this does not include the ability to predict them (Hauhs et al. 2005).

Whereas streams can be rigorously formalized by coalgebraic notions (see, e.g., Rutten 2000) as primitives of a theoretical approach, fluxes appear in the canonical algebraic approach as secondary (derived) quantities.[9] The direction of formalization becomes reversed in this respect as well: Traditionally, one starts with symmetries in the underlying dynamics (of states) and calculates the resulting order in fluxes, and this then has to be validated from observations. Here, we argue for a data-driven approach in which the order and properties of documented streams are used to reach conclusions on the properties of the underlying interactive process. This approach is unusual for natural sciences but quite common in computer science and engineering; a number of theorems are available for inferences about existence and uniqueness in models.

Interactivity is not a new mechanism that can be constructed (syntactically) by adding additional features to an algorithmic machine. In an algorithmic universe in which interaction does not exist, it cannot be generated *de novo*. However, in a universe of discourse in which we allow for interaction, it can be expressed and demonstrated in the form of interactive computing.

INTERACTIVE STREAMS

The next distinction about streams is whether or not they are generated interactively by the system(s) from which they originate. That is, it concerns the way in which the order in their basic events is implemented: by the action of one system alone or by alternating actions of a system and its environment. The above examples of abiotic streams occurring in the environment of ecosystems and many more such as shortwave radiation, transpiration by vegetation, weathering, or precipitation of secondary minerals in rooting zones are all instances of *noninteractive* streams. The widespread use of such terms in ecosystem research reflects the fact that these noninteractive streams can be recorded much more easily than interactive streams.

One may illustrate this situation with chess playing: In the preparations for a chess game, one can either try to reduce the (seemingly?) interactive situation to a noninteractive one (e.g., find a winning strategy, i.e., solve the game algorithmically, read out the complete chess-related memory content of the opponent[10]). Otherwise, one has to cope with the consequences of interaction (i.e., prepare for the game by training and updating ones own memory with relevant content; increase the ability to *evaluate* a board rather than *predicting* it). One promising strategy to be considered is to reduce the interactivity of the game to a minimum by making the opponent's behavior more predictable. This ideal is implied in the frequently heard advice to novice players "always play the board, not the opponent."

We want to grasp the large gap between scientific and empirical models of ecosystems through this analogy: In the natural sciences, by using one of the two definitions/approaches below, an exo-observer (natural scientist) currently has to avoid interactivity completely if she or he wants to achieve understanding and prediction. Ecosystem managers, however, inevitably have to cope with interaction when they want to sustain a service function. Thus, they will get little help from state models when trying to do so. Even worse, any managerial expertise acquired in the form of heuristics has only a dubious scientific status under the prevailing modeling concept that should be replaced later by some proper understanding of processes and is thus often dismissed by ecosystem researchers (Bocking 2004).

There is no easy classification of whether a data stream across an interface *is* interactive or noninteractive. Furthermore, such a classification may change with time and technical progress. The *a priori* classification of ecosystems into the complexity realm (placing them exclusively under dynamic systems theory) narrows the range of possible models. In addition, it may even narrow the model classes considered to a set of unsolvable tasks. Interactivity may turn out to be an illusion when one ultimately acquires the 'true' dynamic representation of an ecosystem, but we do not care as long as interactive simulations are closer to the nature of the managerial problem than models based on dynamic systems theory.

WHAT IS AN ECOSYSTEM IN NATURAL SCIENCES?

Geosciences

Ecosystems can be delineated spatially on the basis of noninteractive streams at their boundaries. An ecosystem in the perspective of *geosciences* has to fulfil two conditions:

- The smallest region whose boundaries can be characterized completely by noninteractive streams.
- The volume included by this boundary contains some systems that are classified independently[11] as being alive (by unbounded behavioral features such as being able to adapt, evolve, or reproduce).

No further conditions for the internal aspects are imposed.

This first definition imposes the existence of an upper cutoff scale for any biological interaction. This definition has proven useful when investigating the relationship of biotic responses to changes in streams at the boundaries within a larger geochemical and geophysical context, as in 'biogeology' or 'biogeochemistry.' It is (implicitly) widely used in monitoring ecosystem response in the context of environmental changes such as deposition of air pollutants or eutrophication.

Biosciences

The second definition aims at avoiding interaction by heading for the lower cutoff scale of life. An ecosystem can be defined secondly on the basis of the noninteractive components. These are components without any persistent states. Their state is a function of external forces alone. An ecosystem in the perspective of *biosciences* is:

- the largest aggregation of noninteractive components

- that maintains across its outer boundary *unbounded* interaction as an irreducible aspect of its behavioral repertoire with the environment
- while using genes as persistent states for maintaining interaction.

No further conditions for the character of the interactive potential are specified here other than that this type of ecosystem appears as a carrier of some unbounded interactions. This may include phenomena such as an ability to evolve new behavior through (open-ended) evolution. The character of models applied to such ecosystems is in most cases direct (i.e., trying to predict functional output or structural change from given input and initial conditions). The technical challenge in direct modeling is the combinatorial explosion resulting from an iterated combination of the basic (noninteractive) building blocks. In general, such models produce too much data. Their outcome is difficult to evaluate algorithmically. Hence, modelers end up with a severe selection problem that is insufficiently covered by the available data set. Living systems appear as structurally too complex.

A number of biological terms can be made more precise when considering life as an instance of interaction: A multicellular *organism* emerges through a coordinated bounded interaction among locally connected cells (Minelli 2004). A species extends the notion of bounded (ritualized) interaction beyond an organism to an interbreeding population. The bounded set of interactions among organisms that potentially leads to reproduction defines a *species*. The interaction with members of other species remains unbounded. This general relationship among species is characterized as open-ended coevolution – used here as our primary example of an unbounded interaction. Hence, the notion of ecosystems in biosciences addresses the difference between bounded versus unbounded interaction, whereas the notion of ecosystems in geosciences addresses the difference between unbounded and 'amnesic' interaction (i.e., noninteraction across functional boundaries).

A reproducing population of biological agents *is* thus a group of agents using DNA as a hidden persistent *state*. No agent outside this group is able to access this memory in any other way than by observing their phenotype (behavior/structure) or interacting with such phenotypes.[12] The fact that the meaning of the persistent states is hidden from external observers and can only become expressed interactively (with a responsive environment) is the reason for the necessity of the genotype/phenotype distinction in biology. This distinction sets biology apart from other natural sciences, especially in terms of models (Rosen 1991). We regard it as a primary signature of interaction.

The geoscience approach is usually chosen when one studies the functional and spatial embedment of living systems into an abiotic environment: Where does life occur, under which conditions? The bioscience approach is usually chosen when one studies the emergence of living behavior: How did it first arise from its nonliving constituents?

WHAT IS A MANAGED ECOSYSTEM?

We have defined life as an (unbounded) interaction in which the persistence of states is related to genes. The interactive modeling paradigm is accompanied by a typical perspective: An agent typically finds itself embedded *within* an interactive network and views interfaces across which interaction occurs from their 'inside.' An interacting agent may look back at *realized* interactions documented in its accessible memory. The role of an interactive *simulation* is to carry a bounded (and possibly complete) representation of the choices that have been reproducible within this interaction. Then, proper actual choices can be judged by the agent against the choices made during the training phase and their corresponding outcomes in the memorized past.

Memory may exist at an individual or collective level depending on accessibility. One could define the 'self-model' of the agent by individually accessible memory and the identity of a culture by collectively accessible memory, though this is beyond the scope of this paper. Here, we are only interested in a small subset of collective memories: those addressing the realized interactions with ecosystems. By definition (see above), the interaction of humans with co-species can only occur *within* the biotic realm of an ecosystem (disregarding the position of its spatial boundaries to their abiotic environment).

Humans evolved from biotic interactions with co-species. Such interaction was initially unbounded and symmetrical as in any coevolution. With the first human culture, a new form of persistence (besides the persistent states of the genome) and, hence, a new form of memory emerged. Co-species were excluded from this human cultural memory and interaction. Hence interaction of humans with co-species became asymmetrical and bounded for the latter from then onward: Humans *domesticated* other species. Domestication can be viewed as a finite set of intervening options by which further evolution in one species can be stopped or directed by another one. Unlike coevolution, it constitutes an asymmetrical relationship among species. The future survival of domesticated species became dependent on human culture.

The role of humans is unique in being almost the only species that is able to domesticate other species and make their survival dependent on cultural transmission. Note that the two definitions introduced above referred to the unbounded features of life (open evolvability). The existence of domesticated species (and related ecosystems) allows us to introduce another, third notion of an ecosystem that refers to bounded interaction. In the case that one succeeds in establishing an ecosystem in which a domesticated species becomes a dominating population (e.g., a field of wheat, or pasture with a herd of cattle), the concept of bounded interaction transfers to the ecosystem. Choice options open for the domesticated species are culturally constrained to a finite set that is exhaustively known to the domesticating human culture. Ecosystem management becomes a mixture of functional and interactive relationships between humans and the system hosting domesticated species. Abiotic streams across ecosystem boundaries, as defined above, are examples in which the functional relationship is appropriate: for example, watering or supplying additional nutrients to an ecosystem. The selection of individuals for breeding is an example in which a bounded interactive relationship holds.

Experts in farming, pasture, forestry, and so forth use the term ecosystem in this third type of meaning. It is the system that they can interactively force into a standardized overall function (Bocking 2004). This interaction is *bounded*; it can be represented in a tradition and can be applied in a sustainable manner. That is why it can be embedded into an external overall function for the civilization of which it is a part: providing timber, fiber, food, and so forth for the society.

The dilemma of the two scientific notions above for an ecosystem is a methodological one. As long as observers remain 'exo-' with respect to the observed system, they will encounter instances of unbounded interaction that occur within it. We conjecture that these phenomena (and the corresponding states) can neither be identified by inverse modeling (geosciences) nor can they be generated *de novo* by direct modeling (biosciences). The rigorous scientist, who strives to study untouched or only experimentally conditioned ecosystems, may not be able to get rid of internal unbounded interaction. This feature will limit and intervene in any predictive modeling attempt. If interaction is taken seriously, the difficulties discussed above appear as a signature of a principal limit rather than as technical difficulties to be overcome by refinements in measurements or more comprehensive modeling attempts.

Successful managers of an ecosystem are able to interactively prevent unbounded choice within the system occurring. If they can demonstrate reproducibility, they have achieved the ultimate management condition: sustainable ecosystem management. The 'price' that has to be paid for this, however, is that managers are inevitably participatory endo-observers for some interactions. Their observations and memories are by no means objective. Here, (interactive) simulation may be a decisive new technology that helps to document, investigate, and disseminate such expert knowledge beyond the idiosyncracies of its origins. The flight simulator example can in this respect be extended into ecosystem management (Hauhs et al. 2003).

A model comprehensively representing a bounded interaction may serve at the same time as the carrier of norms for proper intervention. It may become a basis for the evaluation of new instances of interactions in a similar manner as a minimal (explanatory) model may be the basis of predictions in the algorithmic paradigm. If a chess computer can represent and handle anything (bounded) that might happen in chess, it may also direct a novice to proper moves; if a flight simulator includes anything (bounded) that can happen to the pilot of a specific plane, it can be used for training. If a forest growth simulator includes what has happened in a particular type of forest, it can be used to train thinning operations. In real-world situations, function and interaction may thus occur in a nested manner making them difficult to separate. Ecosystem utilization is an example in which a bounded interaction can be delegated to experts such that the whole system serves a function such as providing food. Note that the embedding relationship between interactive and functional aspects can also occur in a reversed manner. A musical instrument or a lasso (Ingold 1994) are both examples in which a functional tool with complete physical (algorithmic) description can be used by experts to serve an interaction. It can also only be learned interactively.

In interactive computing, simulations do not provide an explanation of what has happened; they do not represent the 'natural laws' governing the true dynamics as in the case of algorithmic models. However, they represent the past choices that may reoccur in a bounded interaction and may hence represent social norms in an intersubjective and novel way. This makes it possible to evaluate rare and decisive situations in a systematic way (e.g., in chess, the aviation industry or forestry).

Table 1. Limits of the two modeling paradigms and how they are related to prominent simulation tasks in science, engineering, and ecosystem research

	Algorithmic models	**Interactive models**
Accomplished tasks	Many examples in physics Reconstructing plant structure (L-Grammar)	Chess computer Flight simulator for pilots
Current limit	Weather prediction	Flight simulator for foresters Assessment of empirical models (e.g., in hydrology)
Out of reach for technical reasons	Assessment of empirical models Predicting forest growth under climate change Open-ended evolution	Flight simulator for nature conservationists
Out of reach in principle	Nothing of practical relevance?	Predicting forest growth under climate change Open-ended evolution 'Flight simulator for God'

The new model type may lead to a very different perception of where to expect technical and fundamental limits (Figure 1; Table 1). Some problems such as predicting an ecosystem response under an altered climate, appeared to be complex but solvable in principle under the algorithmic modeling paradigm: These will be reclassified in the new paradigm, and may become unsolvable in principle. Despite the disappointment that such a result may mean for ongoing research projects (e.g., climate change), in the long term, we consider it a step forward. If a situation is truly interactive in the sense we have used the term here, there is no way to substitute for missing experiences from an open interaction (e.g., if a type of choice or behavior has not occurred yet). This is due to a variant of the combinatorial explosion mentioned already: the mismatch between genotypic potential and actual phenotypic expression. Only an almost negligible fraction of the former can be realized within the lifetime of an organism, an ecosystem, or even a whole species.[13] On the other hand, other problems such as assessing empirical knowledge and expertise in ecosystem management appeared as similarly complex under the old paradigm. Under the new paradigm, these problems may now be within the reach of modern IT.

A different case is nature conservation, a problem that, even with today's IT, may remain technically too hard for interactive simulation models (see Table 1). In these cases, the goal is to keep an ecosystem-wide set of species, of growth potential, or its biodiversity. We still do not know whether this is a management task that can be organized as in forestry or agriculture, or a goal of a different character (e.g., in terms of ethical values). If it becomes a management task, then any *reproducible* measure of success has to be based on *bounded* interaction with technical norms. In other words, successfully managed ecosystems will, under the goal of nature conservation, ultimately become domesticated by halting open-ended evolution. If not, the result of any protective action cannot be judged by its *results*, but rather by its *intentions*. Intent, however, is not an operational criterion for unbounded interactions among different species.

Ecosystems not touched by humans (if there are any), *natura naturans*, cannot be represented by a bounded interactive simulation. Modeling and evaluating their behavior remains elusive under the second modeling paradigm.[14] The anomaly mentioned in the introduction between what should be and what appears to be possible with respect to ecosystem management is thus resolved. The addition of human goals and proper interventions is what makes the modeling problem tractable for *natura naturata* under the new interactive paradigm, whereas human interference has been considered as a disturbance rendering modeling even more difficult under the traditional algorithmic simulation approach.

CONCLUSIONS

Up to now, most simulation models developed in the social and biological sciences still use the algorithmic modeling paradigm. Technically, such models do not leave the realm of dynamic systems theory. These approaches abstract from any interactive aspects of the modeled system. The results are ambivalent and leave ecological (and, as far as we can see, also social) modeling in a dilemma: The models still do not yet deliver contra-intuitive predictions relevant for management. However, these models are very useful when used as communication tools for arguing about the cases studied (Bousquet and Le Page 2004). A model developed for prediction under dynamic systems theory becomes a communication tool when it fails to predict blindly and is thus calibrated to observations. For this purpose of communicating and documenting existing experiences, however, more efficient, interactive simulation tools are available today. As long as various forms of interaction are not defined and studied more rigorously, simulation models may focus on the wrong aspects of ecosystems. While we may still fail to predict ecosystems, we miss a chance of improving their evaluation by experts.

The interactive modeling paradigm provides us with a different and new way of representing human knowledge. It may become recognized as a dual form of the traditional approach. The proliferation of artificial objects resulting from functional and industrial production interested philosophers in the nineteenth century. Today's increase in interactive simulations of artificial (choice) behavior is facilitating communication and sets current technology changes against this historical background of facilitating production. (Interactive) simulation attracts the attention of philosophers of science as documented by this book.

Interaction cannot be created *de novo* in a computer. However, if it is a useful concept, with a promising potential to become a formal rigorous one, some of its existing bounded forms can be *transferred* to a computer. It allows us to abstract from and to deal with a human perspective toward valuation and choice from an endo-perspective. This time, it is not an abstraction with respect to observation (and spatial perspective) as in Renaissance times, but has a memory and a temporal perspective. It may provide areas of professional expertise in ecosystem management with an intersubjective way of documenting and communicating knowledge about bounded sets and the proper order of decisions in certain interactive situations.

In a more general sense, a better understanding of simulation technologies and especially interactive ones may acquire a role comparable with the mastering of perspective in arts. For visual perception, the invention of perspective became a historical stepping stone for the 'cognitive enlightenment' and subsequently modern science. Today's interactive simulation is about to acquire the technical potential for rehabilitating memory (alongside vision) as a similarly reliable source of intersubjective knowledge. In some restricted areas such as chess or flight simulation, it has become a carrier of norms and is already used routinely for training to expert levels. If this approach can be extended to the human relationship with ecosystems, it may trigger a corresponding 'normative enlightenment.'

We have argued above that under this modeling paradigm, it becomes easy and straightforward to define the key notions of ecosystem research and modeling. In addition, it allows us to discuss technical and principal limits, and this seems to give a simple explanation of past successes and failures in ecological modeling. It is at least a complementary approach to the same systems from a distinctively different perspective, and exploits knowledge on them that was dismissed all too quickly in the traditional approach.

Taken together, this seems to be sufficient reason for the distinction introduced above and especially interactive simulation to be taken more seriously by philosophers of science as well. Which modeling tools will yield better results in ecology and ecosystem research will, of course, depend on empirical testing.

[*] *University of Bayreuth, Germany*
[**] *Norwegian Institute for Forest Research, Ås, Norway*

NOTES

1 "The central concept of Newtonian mechanics, from which all others flow as corollaries or collaterals, is the concept of *state*, …" (Rosen 1991).

2 If ecosystems are viewed under dynamic systems theory, one could ask instead: … *despite* continued human interference. However, the search for dynamic models assessing the stability of ecosystems is an old and still controversial field, which we shall not go into here (McCann 2000).

[3] We use the notion of 'skill' in the same sense as Ingold (2000).

[4] Nature conservation may be regarded as an exception. There the management goal is often to sustain an ongoing interaction with 'nature' (see last section).

[5] The presence of noise is unrelated to interactivity. Noise does not make choices by definition.

[6] Representations are often modified with the effect that a model is largely simplified or extended beyond its 'grounding in reality.' In the first case, the model seeks the most concise representation of a state; in the second, the most comprehensive representation of a choice.

[7] However, not every computer has to be an algorithmic machine. There may be aspects in the heuristics of IT engineering that have not yet been properly formalized. Interactive computing can be considered as an example; it is economically important, but not all aspects of it have been given a formal grounding (see Introduction of Turi [1996]).

[8] As used in the computer sciences, particularly in coalgebraic approaches to computational structures.

[9] We tried a formalization of fluxes as boundary-determining objects for ecosystems earlier (Hauhs and Lange 1996). However, this does not lead to any fundamental and concise notion as is possible for streams in coalgebra.

[10] Try this only if it is a computer!

[11] The logic relationships among the attributes usually used to define life remain unclear (Ruiz-Mirazo et al. 2004).

[12] There may be observations of the genotype, but since the mapping from genotype to phenotype is an interactive one, this mapping cannot be identified by observations alone (but requires an interactive approach itself). This leads to the conjecture that the proteomic research program must fail on principal grounds similar to the alchemistic program, that is, failure due to choosing a wrong model category (and hence ignoring limits).

[13] With the possible exception of unicellular organisms.

[14] Whereas explaining their behavior under the first paradigm only appeared to be very difficult.

REFERENCES

Arbab, F. (2005). "Abstract behavior types: A foundation model for components and their composition", *Science of Computer Programming*, **55**: 3–52.

Beven, K. (2001). "On modeling as collective intelligence", *Hydrological Processes*, **15**: 2205–2207.

Bjerkenes, V. (1904). "Das Problem der Wettervorhersage, betrachtet vom Standpunkt der Physik und Mechanik", *Meteorologische Zeitschrift*.

Bocking, S. (2004). *Nature's Experts. Science, Politics, and the Environment,* New Brunswick, NJ: Rutgers University Press.

Bousquet, F. and C. Le Page (2004). "Multi-agent simulations and ecosystem management: A review", *Ecological Modelling*, **176**: 313–332.

Brooks, R. (2001). "The relationship between matter and life", *Nature*, **409**: 409–411.

Goldin, D., S.A. Smolka, P. Attie, and E. Sonderegger (2004). "Turing machines, transition systems, and interaction", *Information and Computation Journal*, **194**: 101–128.

Gumm, H.P. (2003). "Universelle Coalgebra", in T. Ihringer (ed.), *Allgemeine Algebra*, Lemgo, Germany: Heldermann Verlag, Appendix.

Hauhs, M. and H. Lange (1996). "Das Problem der Prozeßidentifikation in Waldökosystemen am Beispiel Wassertransport", *IHI-Schriften Zittau*, **2**: 212–222.

Hauhs, M., F.-J. Knauft, and H. Lange (2003). "Algorithmic and interactive approaches to stand growth modeling". in A. Amaro and D. Reed (eds.), *Modeling Forest Systems*, Wallingford, UK: CABI Publishing, pp. 51–62.

Hauhs, M., J. Koch, and H. Lange (2005). "Comparison of time series from ecosystems and an artificial multi-agent network based on complexity measures", in J.T. Kim (ed.), *Systems Biology Workshop* at the VIIIth European Conference on Artificial Life (*ECAL 2005)*, Canterbury, Kent, UK: University of Kent, 12pp.

Ingold, T. (1994). *Companion Encyclopedia of Anthropology*, London: Routledge.

Ingold, T. (2000). *The Perception of the Environment – Essays in Livelihood, Dwelling and Skill*, London: Routledge.

Jakeman, A.J. and G.M. Hornberger (1993). “How much complexity is warranted in a rainfall-runoff model”, *Water Resources Research*, **29**: 2637–2649.
Kimmins, H., C. Welham, B. Seely, M. Meitner, R. Rob, and S. Tom (2005). “Science in forestry: Why does it sometimes disappoint or even fail us?”, *IUFRO 205*.
Kratz, T.K., L.A. Deegan, M.E. Harmon, and W.K. Lauenroth (2003). “Ecological variability in space and time: Insights gained from the US LTER Program”, *Bioscience*, **53** (1): 57–67.
Lansing, J.S., J.N. Kremer, and B. Smuts (1998). “System-dependent selection, ecological feedback, and the emergence of functional structure in ecosystems”, *Journal of Theoretical Biology*, **192**: 377–391.
McCann, K.S. (2000). “The diversity-stability debate“, *Nature*, **405**: 228–233.
Minelli, A. (2004). *The Development of Animal Form - Ontogeny, Morphology and Evolution*, Cambridge, UK: Cambridge University Press.
Peters, R.H. (1991). *A Critique for Ecology*, Cambridge, UK: Cambridge University Press.
Pittroff, W. and E.K. Pedersen (2005). *Ecological Modeling, Encyclopedia of Life Sciences* (http://www.els.net), Chicester, UK: Wiley; doi:10.1038/npg.els.0003270.
Rosen, R. (1991). *Life Itself – A Comprehensive Inquire into the Nature, Origin, and Fabrication of Life*, New York: Columbia University Press.
Rubin, D.C. (ed.), (1995). *Remembering Our Past – Studies in Autobiograhical Memory,* Cambridge, UK: Cambridge University Press.
Ruiz-Mirazo, K., J. Peretó, and A. Moreno (2004). “A universal definition of life: Autonomy and open-ended evolution”, *Origins of Life and Evolution of the Biosphere*, **34**: 323–346.
Rutten, J. (2000). “Universal coalgebra: A theory of systems”, *Theoretical Computer Science*, **249** (1): 3–80.
Schellnhuber, H.J. and V. Wenzel (eds.). *Earth System Analysis,* Berlin, Heidelberg, New York: Springer.
Schütz, J.-P. (2001). *Der Plenterwald und weitere Formen strukturierter und gemischter Wälder*, Berlin: Parey Buchverlag.
Turi, D. (1996). *Functional Operational Semantics and its Denotational Dual*, Amsterdam: Free University of Amsterdam.
Ulanowicz, R.E. (2004). “On the nature of ecodynamics”, *Ecological Complexity*, **1** (4): 341–354.
Wegner, P. and D. Goldin (1999). “Interaction as a framework for modeling”, in P. Chen, J. Akoka, H. Kangassalo, and B.Thalheim (eds.), *Conceptual Modeling: Current Issues and Future. Lecture Notes in Computer Science 1565*, Springer, Heidelberg, pp. 243–257.
West, G.B. and J.H. Brown (2004). “Life’s universal scaling laws”, *Physics Today*, **57** (9): 56.