THE MODELING APPROACH IN ECOSYSTEM RESEARCH AND MANAGEMENT

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ABSTRACT

The process of model building in the environmental sciences and when dealing with ecosystems is discussed. Two types of modeling approaches need to be distinguished: An algorithmic one, which has been used traditionally in physics, meteorology, and other branches where biological degrees of freedom are either absent or neglectable; and an interactive one, which is a new framework in computer science and seems to be most suitable in cases where organisms (including humans) as agents in ecosystems are to be taken into account. The first modeling approach is exemplified by state models in dynamic systems theory and expresses the correspondence imposed by laws of nature between inferential entailment in a formal system and causal entailment in natural systems. Modeling is to be separated from simulation. In the first case simulation is a less restrictive type of modeling in which the description of non-interactive behaviour is the purpose and no constraints on the correspondence to internal states are imposed. The second (new) modeling approach is exemplified by interactive simulation models. It is able to express the correspondence in behaviour imposed by engineering standards (or cultural norms in general) between documentation, training and application in interactive choice situations such as games or ecosystem management. It generalises the notion of simulation for interactive problems. In an idealised situation the strictest correspondence between behaviour in a natural and a virtual system is expressed as bisimulation. The principles for model building are shortly demonstrated with examples.

INTRODUCTION

The term "model" has a wide range of notions in science. After restricting the focus to environmental sciences, ecosystem research or ecology conflicting meanings remain (Stehr 2001). The widespread and confusing applications of the term "modeling" is similar to that of "force". However, in the case of "force" some very specific meanings have been identified and given formal definitions. It can even be said that the whole edifice of physics rests upon four notions of force and the models derived from the state concept. To what extent is this success story of modeling in physics transferable into sciences dealing with Life? Can model approaches dealing with living entities be formalised and to what extent has that already been achieved? Since modern computing has become cheaply available the term simulation has been used in the same or similar meaning as the term model. What is the difference between modeling and simulation for ecosystem management and its implications?

TWO TYPES OF MODEL REASONING

The algorithmic approach

We start from and base the subsequent argument upon the approach proposed by Rosen (Rosen 1991). However, later it will be necessary to extend the meaning of the term modeling approach to include a second case. Rosen distinguishes between material (natural) and formal realms and two forms of entailment. In the material world events are connected by causal entailment, whereas in the formal world they are connected through inferential (logic) entailment. (Figure 1). The concept of laws of nature is thought to connect the two and to garantee a deep congruence between these two forms of entailment operating upon the actual configuations (states) in the natural and in the abstract realms, respectively. Here we will restrict this correspondence to an algebraic congruence, i.e. the equational forms of laws of nature. In addition to the correspondence imposed by laws of nature the encoding of observations represents a critical link. It is not part of the formal system and requires a way of intersubjective agreeing upon an objective content in observations. It is here where much of the "art of modeling" in the sense of Robert Rosen lies.

A diagram as in Fig. 1 could only be drawn after an inside/outside (or object/subject) distinction has been made, by an observer (modeler) exterior to the natural system to be observed, seeking a way of capturing systems in an efficient way through abstraction. This exo-observer compares two object systems and often acts as a filter - by either neglecting "unwanted"

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behavior or actively preparating the system into defined initial states from which subsequent observations (of behaviour) can be repeated. This is the modeling concept that underlies dynamic system theory and the (Newtonian) natural sciences today (Rosen 1991). It connects these two worlds: the direction from the material to the formal is termed "encoding" (abstracting) whereas the opposite direction is termed "decoding" or realisation. In practical terms, the encoding step is the model building process, providing a system of equations that, when complemented with appropriate static system descriptors (e.g., boundaries) build the formal system. The decoding step is solving these equations for the appropriate system – this step produces model data which are then compared to the observed behavior for a given time period.

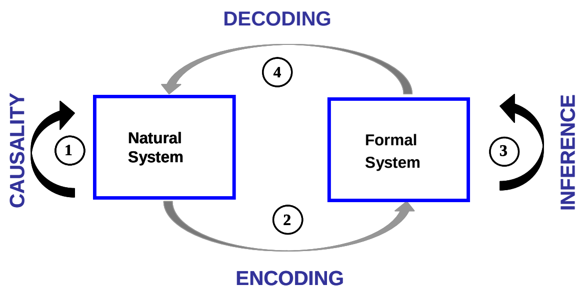

Figure 1: Modeling relation between real and abstract systems (Rosen 1991). This is the modeling approach that is used most widely in natural sciences and sometimes taken even as synonymously with them. The black arrows (1,3) indicate those parts of the cycle that are connected by and corresponding to laws of nature (Rosen 1991). The grey arrows (2,4) indicate the "open parts" in this loop (unentailed in Rosen's terminology).

The nontrivial part of this loop is the encoding. The decisions about changes to be made in the model after observing deviations between model data and actual behavior in step 4 (Fig. 1) are also non-trivial.

The flow between natural and formal system indicated by the arrows is one of data and equations or mathematical abstractions. The latter have *lawlike character*, and the procedure has to be considered as repetitive. Lawlike means that its validity has temporal and spatial extension and stands behind observations being repeatable in space and time. The premise is that the procedure described by Fig. 1 eventually converges, i.e. that the formal system is a proper representation of the real world. It is the fundamental claim of natural sciences that nature is describable by natural laws, emphasizing the crucial role of reproducibility in experiments (Mittelstrass 1995). This is expressed by the notion of Natural Law in the words of Rosen.

The interactive approach

We propose a second type of modeling approach, suitable for interactive systems and their corresponding simulation models as given in Fig. 2. Here, no exo-observer is present, and the flow between the natural system and its virtual counterpart is represented by the observers themselves and their persistent memory when physically switching from one context to the other. Any participating agent in such a series of repeated transitions will be termed endo-observer. However, this diagram is to be drawn only after the system/environment boundary has been delineated for each of them (localization of the system that carries such persistent memory is the precondition for endo-observers). After each endo-observer has been localised one can pose the problem of how their collective memory can be intersubjectively documented.

The participatory agents run through a training cycle with an interactive simulation as part of the virtual system. Thereby the interactive relationship between environmental system and agent behavior is established. This leads to a pattern of actions and reactions which are then applied to the natural system after the endoobserver has (physically) moved back to the other side of the diagram. Usually, there is a mismatch between the trained pattern and the actual interactive relationship of the practitioner with the natural system. Thus, in a second step, the practical experiences are built into a changed description as virtual system. This latter step is the nontrivial one, as there is no obvious way to transform expert knowledge into formal descriptions (source code) in interactive systems. It is also not trivial to classify interactive systems correctly and distinguish them from non-interactive complex signals (see discussion).

Whether this loop converges or not is not a matter of natural laws - it is an active process and it has normative aspects: among all systems and behaviors the trained expert utilizes the most reproducible or stable ones, since these are the only ones he exerts control on. Convergence would imply that the differences in behaviour between virtual and natural system disappear - in sharp contrast to the situation of Fig. 1. In interactive systems such a convergence allows to assign an overall purpose (service) to the behaviour that can be interactively brought to a specific and repeatable outcome by experts. Typically the utilization interest rests upon the ability of experts to (interactively) judge and extend the service available from such a system. The existence of a set of expected reactions for the interactive phenomenon provides the basis for the normative background of any local decision (but this is not a functional one and requires evaluation competence of the expert).

We have argued elsewhere that the ability to interactively extend a service available from ecosystems in an unlimited manner by experts, provides a definition of sustainable use of ecosystems (Hauhs et al. 2003). Criteria to test sustainability cannot be abstracted from the documented state of expertship and expert competence in valuation. For example, sustainability in forestry must be judged by changes in the forest ecosystem and the forester.

Interactive behaviour and the services that can be expressed this way has been studied in an abstract way in computer science. The notion of interactive computation has been derived from many situations where internal states are hidden and cannot even be reconstructed and the interest (specification) of the user is solely on the interactive service, i.e. the way the hidden system responds to inputs and outputs. For these problems the term “Bisimulation” has been introduced (Milner 1989) and extends the notion of observational equivalence into the temporal dimension for interactive systems. The states of a system are termed bisimular, if an external observer is unable to distinguish between them by their input – output behaviour. These states can be substituted with each other with no consequences for the observer.

We are interested in the question whether this notion of bisimulation can also be used to express an underlying link in an (extended) modeling approach, analoguous to the role of laws of nature in Fig. 1. Is it possible that the interactive behaviour displayed in the virtual realm of a simulation model becomes bisimilar with the interactive behaviour displayed in a natural (real) system? Apparently in some areas such as chess playing and pilot training the answer seems to be yes.

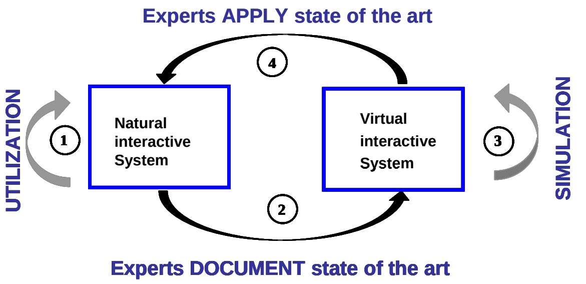

Figure 2: Modeling relation between real and virtual interactive systems. This approach is proposed for models that are capable of simulating interactive behaviour. The grey and black arrows have been exchanged relative to Fig. 1. Here the experts themselves physically move between the virtual and natural systems. Hence it is their consistent behaviour between training, application and documentation that links the cultural norms (standards) in natural and virtual systems. The grey arrows (1,3) indicate the open parts in this loop. It is here where the interaction takes place. These parts are by definition outside the range of algorithmic functions.

In such technical applications, the ultimative goal is that the expert’s abilities are equally valid both in the natural and the virtual system, and that the expert is no longer drawing a distinction between the two. The foremost example in this direction may be flight simulators.

In the following section we will inspect the numbered steps within Fig. 1 and 2 more closely. Examples for the two types of modeling approaches will be given when we try to integrate the two cases into an approach that generalises the one proposed by R. Rosen.

STEPS IN MODEL BUILDING AND COMMUTATIVE DIAGRAMS

The algorithmic approach

The graphical illustration of the modeling approach in Fig. 1 was chosen by Robert Rosen to intentionally resemble a commutative diagram of algebra, where the objects are the natural and the formal system and the encoding/decoding are the morphisms. The reasoning and logical inference of model building for systems amenable to an algorithmic representation is outlined in Fig. 3.

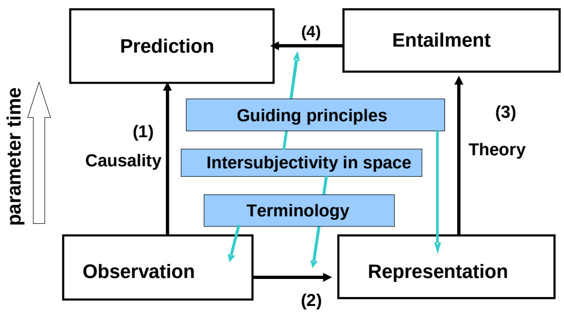

Figure 3: The process of model building for state systems

At the starting point we have observations (as made by an exo-observer) from a given system at a given time (period). The natural system develops over time from an initial state to a future state (path 1) in a causal way. This temporal evolution is accessible through local observations of the system for (at least) one additional point in time. This is indicated by the box “prediction”.

The crucial point here is that time is solely a Newtonian parametric one; the system is considered to be invariant with respect to time shifts. This opens the possibility to reproduce experiments by reinitialisation. The usually presupposed additional spatial translation invariance is less significant here, although we are for both algorithmic as well as interactive systems mostly interested in aspects not unique to the system.

In the context of these systems, only those observations are scientifically valid that are to a high extent observer-independent, communicable, not relying on individual perspectives: they must be *intersubjective*. Abstraction e.g. from the individual competencies in handling measurement devices (say) is mandatory. We are aware that this is an idealization but stress the point that for interactive systems, this is an impossible requirement.

The formal representation of the observations (path 2 in Fig. 3) has to use a terminology agreed upon in the scientific community; it will typically involve objects, forces, and spatial configurations. When observations become encoded into state variables one has successfully abstracted from the histories. Each branch of natural sciences has its own standard set of referents.

On the right side, one seeks a minimal model ("representation"), from which inferential entailment is most comprehensive. From a fixed set of axioms ("laws") and constraints the exo-observer hopes to cover a maximum of reproducible observations.

The inferential entailment (path 3) is the proper model building (the encoding procedure from Fig. 1). Out of the almost infinite set of choices among models, the scientist selects according to guiding principles. These comprise symmetries of the investigated system, associated conservation laws, restrictions of forces according to the observed variables, imposed initial and boundary conditions, parsimony considerations, and ultimately also aesthetic principles ("this theory is too beautiful to be wrong"). For well-established theories, these constraints reduce the remaining model space drastically.

The algebraic model allows to infer (simulate) the temporal development, starting with observational data, and a later comparison with the same set of observables as measured again from the real system (path 4). This predictive power of the model is most pronounced if there are counterintuitive phenomena in the formal system which are later confirmed by observations. The reference for a counterintuitive phenomenon must at least be partially be grounded on observation.

One example for the latter is sudden instabilities or phase transitions in well-controlled lab-scale systems (like the onset of ferromagnetism), another one the detection of celestial bodies like Neptune from a careful perturbation theory analysis.

The illustration of Fig. 3 implies a scientific program, which iteratively runs through the loop to enhance the model. This program may be considered as successful once the mismatch between observed and predicted phenomena disappears in practical terms. When (and only if) this is achieved, the diagram of Fig. 3 *commutes*: the sequence (2) → (3) → (4) leads to the same result as the direct temporal development (1):

$$(2) \rightarrow (3) \rightarrow (4) \Leftrightarrow (1) \qquad (1)$$

However, the commutativity requires predictability, which is a property of the investigated natural system rather than the procedure described here.

Robert Rosen speaks about simulation when the correspondence of internal structures between natural and abstract systems is sacrified. A simulation mimics the (non-interactive) behavior of a system, without necessarily having any synonymy of elements and their causal entailments in the physical system and the symbols and inferential entailments in the simulation. The drawback of simulations is that due to this lack of synonymy, one cannot learn much about the system under study by examining the internals of the simulation. Simulations try to reproduce (non-interactive) function rather than structure.

The interactive approach

For interactive modeling we need to extend Rosen's notions of model approaches and of simulations.

The commutative diagram derived in Fig. 3 is given another interpretation in figure 4. The criterion whether commutativity was achieved in Fig. 3 is the congruence between predicted and observed system states in the upper left box. For interactive systems and an endo-observer participating in virtual and real interactions this criterion cannot be applied, as the base reference ("truth", the observations in Fig. 3) is non-existing. Here the notion of bisimilar behaviour replaces that of congruent states (observable configurations). The test itself must therefore be extended in time as it may relate to a whole series of interactive decisions.

That is why we put (expert) memories in the lower left box of Fig. 4 instead of observations. Clearly memory (even if we refer to some vague standards of expert knowledge) is a much less well-defined concept than observation. Let us assume for the moment that this difference reflects just the historical situation and we know that in earlier days of modern science observations were regarded as highly dubious, too.

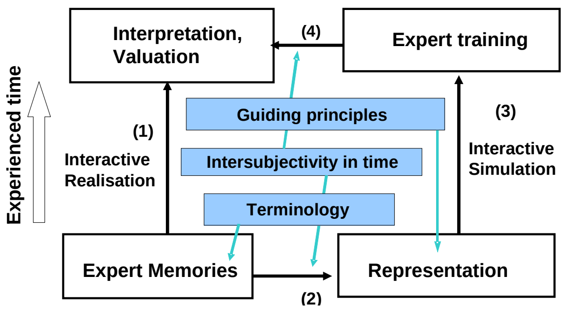

Figure 4: The process of building a simulation model for interactive systems

We will regard the iterative movements of experts through the cycle as the test by which their memories become intersubjectively documented. The enconding

(2) and decoding (4) steps, which were the problematic ones in Fig. 3, become trivial in this case. The experts themselves physically move between the natural and virtual systems and their memories are assumed (by definition) as persistent. However, the entailed steps reflecting the action of laws of nature before, steps (1) and (3) in Fig. 3, are now the open and unentailed sequences of interactive decisions. By definition no algorithmic model is able to encompass the complete sequence as it unfolds (Wegner and Goldin 1999), though they clearly can cover each single step within it (exemplified by a chess computer).

Simulation in algorithmic and interactive problems

In simulation models for algorithmic systems, the main emphasis is devoted to mimicking the non-interactive behaviour of the dynamic system. A typical example from environmental modeling are neural net simulations. Such models do not yield an understanding of internal mechanisms, e.g. of water flow through ecosystems. They have been useful, however, in characterizing the relation between input and output data. (Küppers and Lenhard 2004) argue in a parallel paper that even in this restricted context the heuristic component in the practical building of a simulation model cannot be completely reduced to scientific understanding

This situation changes when interaction is taken into account. For these problems a formalization of behaviour has been proposed, as it is no longer possible to derive it from a closed algebraic system of equations (Goldin et al. 2003). Interactive systems are in a fundamental sense open and thus different from algorithmic computing where the environment is excluded between input and output events. Once an oupt has been achieved by an algrorithm, its internal state must be reset before the next input may occur, hence such algorithmic systems cannot have persistent memory. A Turing machine that is not reset to a predefined initial condition and thus may contain persistent internal states between output and subsequent input events is termed "persistent TM" and has been proposed as a formal model of interactive computing (Goldin 2000).

Persistent states of such a machine are typically inaccessible for an external observer and the only criterion for comparing states is observational eqivalence: Bisimulation. The theoretical results in computer science based on this concept suggest that an approach starting from behaviour is the appropriate one for interactive systems, whereas starting from internal states is appropriate for state systems. Formally, the theories derived for interactive systems are coalgebraic duals to the algrebras that express the equations of laws of nature.

Undoubtedly, dynamic system theory so far is the dominating approach. Its theoretical framework is fully worked out, whereas for the interactive approach we basically have a number of promising starting points, which are, however, interesting epistemologically. In the last section we will discuss how both approaches could be accomodated into a joint scheme.

MODELING IN SCIENCE AND TECHNOLOGY

We consider the ideal situation that commutativity has been achieved in both Fig. 3 and 4. Robert Rosen has discussed why the first modeling approach is often regarded as synonym with natural science itself, though neither he nor we share that opinion. However, we will use this strong label here to make the difference clear between the two cycles.

Commutativity implies a correspondence between arrows 1 and 3 in Fig. 3 and 4. That is why these arrows (indicated by numbers and colour) are shown in parallel in Fig. 5. In the lower case, we are dealing with exo-observers and non-interactive dynamics. The area indicated as the realm of laws of nature ("Science") can be regarded as given systems; modeling is inference on it. The open part of this modeling approach (grey arrows) is where ideas and creativity comes in: the parts dealing with encoding and decoding operations. The goal is to express laws of nature in their most simple form as equations.

Once an object has been thoroughly understood, science is able to reproduce the observations. Eventually, science may turn into technology: when further repetitions no longer have the purpose of demonstrating understanding, but rather achieve a desired functionality. The label "science" should thus be read as an indication that it started from a scientific objective for which this modeling approach is typical.

Commutativity in Fig. 4 implies a correspondence between the experts' response in a virtual training situation and their response to a real/natural system. Here it is the participatory and open parts of the cycle that are shown in parallel. They are linked by cultural norms. Through these norms, overall functions (services) are defined for the expert: getting food, timber, etc. from an ecosystem, being able to win a chess game, flying from A to B are a few examples. This provides the final causation typical for technology (Rosen 1991).

The building and documentation of the model is in this case a more formal procedure. For any documented and achieved service one can ask whether this response has already been covered by the simulation model. The purpose of the model is not to provide the most simple explanation, but the most comprehensive repertoire of all possible behaviours that had already been encountered in the managed natural system. If in our idealised case commutativity has been achieved, then the model can be regarded as complete. A symptom of completeness is when experts are no longer able to distinguish between the interactive system and its model ("Am I playing a human or a chess program?"). This is the equivalent of the Turing test for interactive systems.

Documentation reduces here to the inclusion of additional potential behaviour in the model, in cases where the last cycle does not confirm the congruence relationship. Application reduces to the training of novices to everything that might happen in this system and judging his/her performance in the training environment.

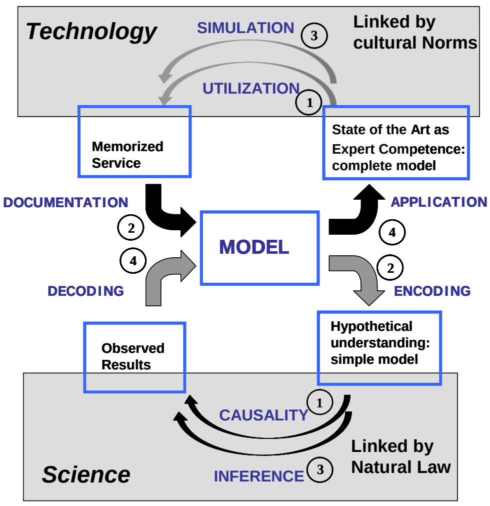

Figure 5: The two modeling approaches combined. In the upper cycle interactive simulation and utilization (e.g. of ecosystem services) is closely related in an idealized (sustainable) Technology. In the lower cycle causal structure in real systems and inferential structure in formal systems are merged by an idealised science. The lower cycle alone is Rosen's modeling approach which is here extended into the upper half to cover also simulation of interactive behaviour.

When a complete model exists, i.e. the most comprehensive competence is included, the interactive simulation proceeds with the same theoretical rigor as the most simple explanation in the scientific modeling approach.

Chess serves as an example. Complete understanding can be achieved in two ways. The first one is to find a winning strategy. In this case the interactive aspects can be shown as virtual, it will cease to be a game. This corresponds to the scientific modeling approach, where the problem is ultimately reduced to function. The second possibility is to derive a complete model of human heuristics in playing. This program would contain all constraints of human playing, it could be beaten, but no more by any single human, only collectively by all of them (i.e. by another program of the same type). This interactive model would be able to simulate and master anything that can happen in human chess playing. A novice could be trained to any level by just playing this simulation. This second case shows the technology approach where the heuristics of good playing can never be substituted by scientific understanding. In the contrary who would doubt that the complete model represents some "understanding" of the human way to play the game heuristically? Both cases may still occur in real chess, but the second one seems currently a bit more likely.

EXAMPLES FROM ENVIRONMENTAL MODELING AND ECOSYSTEM RESEARCH

An example of the modeling approach of (non-interactive) environmental science is discussed in the paper by Küppers and Lenhard (this proceedings). That is why we will restrict the examples to cases where living systems are directly involved. We regard ecosystem management as a paradigmatic one. Humans have not fully emancipated from the necessity to utilize ecosystems and it is unlikely that they ever will. In addition science has not achieved an understanding of Life that would allow to reconstruct it by the modeling approach depicted in figure 3 in science from its building blocks. It is also unlikely that this will change in the future. Robert Rosen has argued that there are principle difficulties to be solved.

A political goal addressing this issue is expressed by the notion of sustainability with respect to ecosystem utilisation. One of the best investigated examples is forestry in Europe, where the term sustainability has been used for two hundred years. Under the given environmental conditions and given the range of species in Middle Europe, forestry involves a rotation period of typically a century. Many of the management decisions that are necessary in the course of such a rotation period can only be taken interactively. The current situation has to be judged competently and appropriate action be taken in response to it. We have argued elsewhere that this interactive aspect in silviculture is irreducible, and simulation models of forest growth have thus to incorporate these interactive decisions. (Hauhs et al. 2003).

DISCUSSION AND CONCLUSION

Two complementary approaches for modeling a natural system have been introduced. The first one is widely known and recognized as the prototype of scientific modeling. We suggest that a dual second modeling approach has become possible since the proliferation of interactive computing software, with flight simulation or silviculture as examples.

These two approaches have been sketched as two dual (idealised) cases in a generalised modeling scheme (Fig. 5). An unsolved question is what decides in a given context whether the upper or lower loop is more appropriate. The notion of interactivity is closely connected with complexity. A system that behaves very regular (too simple) or entirely unpredictable (too random) is no candidate for an interactive relationship. Hence interactive systems must appear as complex to any participatory observer. Like explaining complexity, modeling interactivity is thus a notion that depends on both systems that become connected.

Human culture contains examples in which complex environmental signals were mistaken as indicative of an interactive relationship. One of the most prominent example is the annual flood heights of the Nile. Even by todays standards this has remained among the most complex signals known to hydrologists and its nature is still discussed. This single factor has been responsible for the Egyptian economy through its long history. The annual yield could be estimated by the Nile height and the Nilometer was used to set the tax level for the year.

If a complex signal is erroneously interpreted as resulting from interaction it may block a proper understanding of its causes. However, at the other extreme is the complementary situation when one only tries to reduce an interactive situation to a functional one, but this is impossible in principle. This attitude could be exemplified by somebody focussing on finding a winning strategy in chess instead of learning how to play properly. Environmental research over the last two decades can be placed into this realm (Hauhs and Lange 2004). In the case of climate modeling the scientific option is probably the only feasible one and has been taken very far (Küppers and Lenhard 2004). Ecosystem research as started in response to regional environmental changes such as acid rain is a much more problematic one. Here a plentitude of modeling approaches has been investigated and it is still open what will be the most appropriate approach. In any case, a better understanding about the nature of and the choice in the modeling approaches available will help to clarify the situation.

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