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Chapter 2: Modeling frameworks, paradigms, and approaches

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1 Introduction

This chapter provides a general conceptual background to the more specific discussions of GIS-based environmental modeling presented in this book. It addresses three main themes central to environmental modeling: spatial models, complex systems, and geocomputation. The discussion covers static and dynamic, discrete and continuous, and social and natural system models, and helps put in perspective the diverse modeling approaches and issues presented in the following chapters. This chapter highlights the 'systems' perspective with an emphasis on spatio-temporal environmental systems representations. General classes of models rather than any specific ones are discussed, in particular, systems dynamics models under the 'top-down' paradigm, and cellular automata and agent-based models under the 'bottom-up' paradigm.

1.1 Environmental models in research and policy

A model is an abstract and partial representation of some aspect or aspects of the world "that can be manipulated to analyze the past, define the present, and to consider possibilities of the future" (Smyth 1998, p.191). According to other definitions, models are devices for producing missing data about the past or the present, and for anticipating data about possible futures; or, as one great 20th century physicist put it, they simply are frameworks for organizing knowledge. Note that these latter definitions do not presuppose that models must resemble the real world in any form or fashion: indeed, for some model theorists, the 'real world' is nothing more than the universe of potentially acquirable data (Zeigler et al. 2000). This non-committal view allows us to skirt the difficult philosophical question of what the world is 'really' like, helps explain why very different models of the same phenomenon may be equally 'true', and focuses our attention on the performance of models as predictive or explanatory devices.

More specifically, what do we mean by 'environmental' models'? Any aspect of the Earth's environment may be the focus of environmental modeling: a definition can hardly get broader than this. Atmospheric and hydrological processes, land-surface - sub-surface processes, biological and ecological systems, natural hazards, ecosystems management issues, are all popular themes. Environmental models cover a full range of geographic scales, from the local to the regional to the global. Moreover, they cover a wide range of input domains: natural and human, biotic and abiotic, atmospheric, oceanic, terrestrial and socioeconomic. Because the environment is a synthesis of all these domains, environmental models often combine several aspects from one or more of these areas. Thus we have models of the effects of climate change on biota, of fire and forest regeneration, of the interdependence of hydrology and ecosystems, of atmospheric circulation and industrial pollution, of fisheries under the impact of different fishing policies.

There are many reasons why interest in environmental models has greatly increased in the past decade or so. Mounting environmental consciousness in the industrialized regions of the world and an increasing interest among public and private funding agencies to support modeling work related to environmental issues have attracted large numbers of capable researchers. At the same time appropriate techniques, computational resources and especially data of suitable quality and quantity have become widely available, so that the gap between the desirable and the feasible in environmental modeling keeps decreasing. GIS, with its power to integrate diverse databases, undoubtedly played a key role in this development and has become the core technology of environmental modeling research.

While environmental models integrating natural processes have already achieved a certain maturity, those seeking to combine human and natural processes are still in their infancy. It is fair to say that today's frontier in environmental modeling lies at the natural-human interface: this is where some of the most important problems and some of the more interesting research issues are to be found. Researchers and funding agencies alike seem increasingly willing to invest in such cross-disciplinary research, despite the still strong institutional and intellectual barriers separating academic fields. Major examples of integrated human-natural environmental modeling research recently funded by the U.S. National Science Foundation include the two Urban LTER (Long Term Ecological Research) projects at the University of Maryland and the Arizona State University (see http://baltimore.umbc.edu/lter, http://caplter. asu.edu), and some of the projects from the 1998 "Urban Change" competition (see, for example Alberti 1999 and the UCIME project at http://www.geog.ucsb.edu/%7Ekclarke/ucime/). Similar efforts are underway in the Netherlands (White and Engelen 1999) and other European countries.

1.2 What makes a 'good' environmental model?

Environmental models are developed for research or policy purposes. While the line between the two is a fine one in applied fields, there are certain criteria that make a model more suitable for one or the other purpose. All models must be built on good science, they all need to be based on good data, and they all must deal with good problems. Research models are expected to exhibit a higher degree of scientific rigor and to contribute some original theoretical insights or technical innovation. In policy models originality is less of an issue (often, the more 'tried and true' a model is, the better!) but transparency, manipulability, and the inclusion of key 'policy variables' are especially important. Clearly, research models can have significant policy implications (as is the case with the global climate models developed in the past decade) just as policy models can make original contributions to the science of environmental modeling. The next two sections will help clarify these points. Section 2 discusses the characteristics and aspects of environmental models while section 3 focuses on the systems and sub-systems that are the objects of modeling. Starting with the key role of GIS, section 4 extends the discussion to the contribution of *geocomputation* to both research and policy-oriented environmental modeling. Finally, section 5 concludes with the brief review of the accomplishments and future challenges of the field.

2 *The nature of environmental modeling*

2.1 Characteristics of environmental models

Environmental models make up a distinct family different from other classes of models in either the natural or the social sciences. They tend to be data-intensive, cross-disciplinary, dynamic and complex. They often integrate subsystems from several different domains without the support of widely accepted theoretical frameworks to lend credibility to the attempted synthesis. Needing to have explicit spatial as well as temporal dimensions increases their complexity. They depend on data of very variable quality gleaned from a wide variety of sources. As a result, they face issues of uncertainty and fuzziness to a greater extent than either traditional natural science models, which deal with more homogeneous, usually 'cleaner' data sets, or than social science models, which often aim at producing qualitative rather than strictly quantitative results. Moreover, because of their direct or indirect policy implications, environmental models don't have the right to be wrong!

2.2 Facets of environmental modeling:

Clearly environmental modeling presents special challenges. Distinguishing the wheat from the chaff is not always easy. This is why it is all the more important for model builders to be aware of the different paradigms and approaches that underlie the wide variety of environmental models competing for attention and funding these days. This section outlines a general framework to help put such models in perspective and to help recognize the strengths and weaknesses of each. It is based on Smyth's (1998) framework for general geographic modeling adapted to the environmental domain.

According to Smyth (1998, p. 192) it is convenient to think of the modeled world as a *microworld* defined by an *ontology* consisting of contents, spatial structure, temporal structure, 'physics' (rules of behavior), and rules of inference or logic. The notion of an artificial world or microworld, borrowed from AI, is useful for reminding us both that models are not the real thing, and that they need to be internally consistent. A closed microworld is autonomous in that the behaviors within it are completely specified through its initial definition without further reference to the external world. A traditional cellular automaton model (see section 3.2.2 below) is a good example: once the initial conditions, neighborhood template, and transition rules have been specified, the model will enfold all its possible behavior independently of anything external. Other closed microworlds well known to geographers are the classic models of location and land use proposed by Christaller, von Thuenen and Weber. Similarly, ecologists are well familiar with simple predator-prey models that work out the evolution of interdependent populations within predetermined environments. Most environmental models however correspond to open microworlds, admitting elements, relationships, causation, and spatio-temporal and logical structure from outside of their ontological specification (Smyth 1998 p. 193). More commonly these are referred to as open systems though this terminology is less clear about the fact that it is the model, rather than the part of the world modeled, that is 'open'. Once the ontology of a model has been clarified it must then be expressed in a formal system which will eventually be translated into a computational model and a concrete implementation.

The first things defining the ontology of an environmental model are the *entities* within it. For example, in an integrated urban-environmental model, the entities may be roads, built-up areas, different categories of land uses, streams, slopes, bodies of water, forests, wildlife populations, and the like. These will most conveniently be modeled as objects though other representations are possible. Entities primarily have an identity on the basis of which their other aspects can be defined. Relevant aspects of entities include: versions (alternative descriptions that may indicate uncertainty as to some properties of an entity: which western boundary of this urban area is the correct one for 1990?); class membership (about which there may be confusion: is that patch pine or spruce forest?); alternatives regarding the attributes and spatial and temporal descriptions of these entities; and the structures and configurations (e.g., hierarchies of different kinds) that may relate the different entities in an ontology. Anderson classes of land use/land cover are a well known such hierarchy whereby classes are subdivided into more and more detailed categories ('aggregation hierarchy'). Another kind of hierarchy binds together elements that compose a whole. For example, an ecosystem can be decomposed into its constituent entities (forest, grassland, water bodies, soils, animal and plant species, etc.).

What entities will be included in an environmental model will depend to some extent on its intended principal use, i.e. research or policy support. A policy-oriented model must involve entities and attributes of entities that can be manipulated by policy makers ('policy variables'). For example a slope cannot be manipulated but a road network can; the age of a tree stand cannot be manipulated but its acreage can; and so on. A good policy model will include policy variables that have a significant effect on the behavior of the model. Observing how the microworld is affected by manipulating these variables can give decision makers insights into how to act in the real world. Such requirements for practically 'useful' variables do not apply to models developed primarily for research purposes where description, explanation or prediction are the main goals.

The *spatial and temporal structure* of geographic models in general has been the subject of considerable research (Egenhofer and Golledge 1998). Several kinds of conceptualizations and frameworks have been proposed for both space and time. Of special interest to the present discussion is the fact that environmental models typically consist of several different modules or subsystems, each based on its own spatial and temporal framework. Problems may arise when these frameworks are very different and perhaps inconsistent with one another in terms of scale, metricity, topological structure, reference frame, and other such properties.

The *physics* of a microworld are the rules of evolution of entities and of interaction between or among entities that determine what can happen within it: they govern the possible behaviors of a model. These rules may be expressed mathematically, e.g. in the form of differential or difference equations, or computationally, in the form of ‘if-then’ statements and other such specifications. In a physical model the physics (no quotation marks) are literally based on actual physical theory (e.g., fluid dynamics, mechanics, electromagnetism, or the theory of chemical interactions) but in most other cases (and models) the term is to be understood metaphorically. Environmental models often include modules or sub-models backed by the rigor of physical theory but being strongly cross-disciplinary and synthetic, environmental science (and modeling) is by and large a theory-poor domain. This means that a typical environmental model will mix together several kinds of ‘physics’ (with quotation marks), some based on causal hypotheses (A appears to cause B), some on statistical regularities (A is statistically associated with B), others on empirical rules of thumb (when A, usually B), others still on arbitrary rules of behavior specified by the modeler (if A is the case, then do B). Combining such a variety of partial ‘physics’ into a whole free of internal contradictions is a delicate task for which few guidelines exist, and which becomes more challenging as the aspects to be brought together are drawn from domains more remote from one another. Thus it is one thing to integrate a sub-model of rainfall with one of runoff to determine flooding potential in an area, and quite another to combine a model of job growth and one of species extinction into a framework for exploring the environmental effects of urban development.

The *logic* of a microworld completes Smyth’s (1998) pentad of a model’s ontology. This is what allows new facts to be deduced about a microworld from a given configuration. In the case of mathematical models the logic is indistinguishable from the physics as they are both implicit in the formalisms used. In the case of simulation models however the two are distinct. For example, the logic may include default rules to help decide what will happen in situations where behavior is under-determined (e.g., in case of a tie), or to help determine which aspects of a microworld must be changed in order to eventually reach a configuration with specific properties. The latter kind of question is particularly pertinent in policy-oriented models where the interest is not just in possible futures but also in desirable ones, and in the means necessary to reach these. Several formal logics have been developed that in principle can provide rich enough inference mechanisms for environmental simulation models. Most of these are quite complex however and not yet widely used (Worboys 1995). There will be an increasing need to study the logics of environmental modeling microworlds as more models are developed integrating drastically different kinds of processes (e.g., socioeconomic and physical). Formal modeling theories such those by Zeigler (1976), Casti (1997) can greatly assist the development of logically coherent environmental microworlds, as can the closely related perspective of systems theory, briefly discussed in section 3.1 below.

Smyth’s model specification sequence involves, in addition to the choice of an ontology (1), the following steps: (2), expression of the ontology in a formal system; (3), development of a computational model of the formal system; (4), realization of the computational model in a concrete implementation (Smyth 1998, p. 204). These topics are explicated in detail in other chapters of this book and will not be further discussed here. As we will see in section 4 recent computational advances have largely blurred the distinctions among the steps of this sequence. Logically however all these aspects remain a necessary part of modeling even if they do not constitute explicit, separate steps.

3 Complex environmental systems

3.1 System theory: philosophy and key concepts

In this section the emphasis shifts from the model to the system modeled. This is a subtle change of focus since ‘the system’ is itself a kind of model: we model an environmental system that is a representation of some part of the real world. The word ‘system’ goes back to the ancient Greeks and literally means something that hangs (or stands) together. In its modern scientific usage a system is something made up of a set of elements and relations among these elements. This may sound vague but in fact many systems can be defined very precisely by families of differential or difference equations where the variables are the elements and the relations are defined by the mathematical operations on the variables. More generally the elements of a system are the entities in a microworld’s ontology and these are connected to one another through relations of causation, influence, or dependence that together determine the physics of that microworld. Positive and negative feedback, stimulus and response, activation, inhibition, and so on are more specific terms for different kinds of relationships in a system, usually quantifiable. These, along with characterizations of behavior such as self-organization, steady state, instability, oscillation, emergence, and chaos have become an integral part of the system modeler’s vocabulary. What is less well known is that these technical terms have strong philosophical underpinnings in the work of Ludwig von Bertalanffy (1968) dating from the 1930’s. Being a theoretical biologist von Bertalanffy was aware of the limitations of the reigning reductionist paradigm (i.e., the attempt to reduce all scientific explanation to physical laws) in helping describe and explain living things. His General System Theory, composed of system science, system technology, system philosophy, and system epistemology, was proposed as a new way of thinking about, or paradigm for, the kinds of complex phenomena that biologists and other modern scientists in both the natural and the social sciences were studying. Von Bertalanffy’s key insight was that there are laws of systems *qua* systems, in the abstract, regardless of the domain (economics, engineering, ecology, biology, physics, sociology, and so on) from which particular applications may be drawn. This was a highly ambitious program aiming at unifying all science under the systems paradigm. That integrated environmental modeling is possible at all is evidence of the basic correctness of general system theory’s key premise – that systems behave like systems no matter what they are made of. A number of broad methodological concepts such as systems thinking, the systems approach, the systems perspective, etc. have been derived from principles of General System Theory. Their proponents make fine distinctions between them that need not concern us here.

Wilson (1981) following Weaver distinguishes three basic classes of systems. *Simple* systems have few components and few variables (e.g., the solar system) and are studied with the traditional methods of classical physics. Systems of *disorganized complexity* have very large numbers of components and variables but the couplings between them are either weak or random. Gases are typical examples of such systems which are studied primarily with statistical methods: hence the field of statistical mechanics and theoretical principles such as entropy maximization. The third class is that of systems of *organized complexity.* These systems too have large numbers of components but there are multiple couplings and interactions among them that need to be considered explicitly. In these systems, 'the whole is more than the sum of the parts', meaning that their properties cannot be deduced from an understanding of their components. These systems of organized complexity are the ones the systems paradigm is specifically concerned with. Research into *complex systems* of all sorts has flourished in the second half of the 20th century and has stimulated the interest in the study of environmental systems, which provide some of the most challenging examples of complex systems known.

There are two complementary methodological and theoretical approaches to the study of complex systems. The first is the top down approach, exemplified by *systems analysis* and *systems dynamics*. The second is the bottom-up approach, emphasized in *complexity theory*. Both are directly relevant to environmental modeling and are briefly outlined below.

3.2 Environmental phenomena and complex systems

3.2.1 The top-down approach: decompose and conquer

More familiar than General System Theory is systems analysis, one of the many fields under von Bertalanffy's original paradigm. Systems analysis gained prominence after World War II primarily through the spectacular successes of engineering disciplines in building and controlling very complicated systems, from guided missiles to computers. At the same time systems analysis and the closely related field of operations research were being applied to 'soft' fields such as planning, management, and the modeling of human decision making. The possibility to apply the same basic concepts and methods to natural, engineered and social systems was thus practically established. An excellent though somewhat dated introduction to systems analysis for environmental scientists, addressing both natural and social systems, can be found in Wilson (1981). More abstract but still readable expositions of systems theory and systems analysis are found in Casti (1989) and a variety of other sources.

The basic principle behind systems analysis is that complex systems or problems can be decomposed into simpler sub-systems (or sub-problems), which themselves may be subdivided into even simpler sub-sub-systems, until a level is reached where the component parts may be treated as elementary. This approach differs substantially from reductionism in that the focus is not on the elementary components but on the relationships among components and assemblies of components at and between the levels of the (de)composition hierarchy. For example, in an ecological model, a spatial-scale decomposition may consider the interactions of individual organisms within patches at one level, and of populations in an ecosystem at another level, the ecosystem being much more than a sum of ecological patches. (By contrast, in a reductionist ontology, the focus would be on aggregation hierarchies that allow properties of entities at one level to be generalized into properties of groups of these entities). Systems analysis may be static, clarifying the internal structure of a complex system, or dynamic, seeking to derive forecasts regarding future system behavior. This latter case is embodied in the paradigm of systems dynamics.

The history of modeling large-scale systems dynamics began in the sixties with the publication of Forrester's series of three, increasingly ambitious simulation models: Industrial Dynamics, Urban Dynamics, and World Dynamics (Forrester 1975). The latter is one of the earliest integrated environmental models developed, bringing together global population growth, agricultural food production, industrial production, pollution, etc. (however, *World Dynamics* was not a spatial model). Each of these models consisted of several major coupled subsystems, which in turn included large numbers of linked components. Forrester's models were heavily criticized at the time but made some lasting contributions to complex systems research. Of particular relevance to environmental modeling was the demonstration that complex dynamic models of integrated systems could be built with the same basic techniques and vocabulary used in modeling a variety of physical systems, thus opening the way for the integration of social and natural science modeling. Coupled system models in the tradition of Forrester's are still routinely used. The widely popular modeling platform STELLA® is a direct implementation of Forrester's approach and several texts are available to teach related methods (see Odum and Odum 2000)

Most systems dynamics models represent phenomena in analogy with complicated hydrological cascading systems, where *flows* (of matter, energy, animals, people, money…) move between *storage compartments* within which these quantities are created or transformed. Storage compartments are connected to one another through the flows which are resolved into outputs (quantities flowing out of one compartment) and inputs (quantities flowing into another). Most such models assume an external compartment representing the 'environment' of the model, i.e. the rest of the world within which the system studied is embedded and where some of the flows originate and end ('open' systems). In physical systems the transfer and storage of mass and energy is governed by two groups of physical laws: laws of conservation and laws of transport (also called process and flow laws). The logic is the same for social and ecological systems although there are no corresponding rigorous laws of process or flow for these. Discrepancies in the degree of reliability of physical, biological, and social-science model sub-models of environmental system models constitute one of the challenges of integrated systems modeling.

3.2.2 The bottom-up approach: complexity theory

Mathematically, complex systems are characterized by multiple non-linearities and feedbacks. Physically, these formal properties are associated with active exchanges of matter, energy and information between systems and their environment. These characteristics of complex systems often lead to phenomena such as self-organization, chaos, adaptation, emergence, lock-in, bifurcating trajectories, and other types of surprising and unexpected behaviors unknown to classical science. In the late 20th century a 'new' science of complexity developed around the study of these interesting types of dynamics. The 'new' science of complexity and its hallmark phenomenon, chaos, produced a long series of articles and books that captured the imagination of scientists and lay people alike (Waldrop 1992). The Santa Fe Institute was founded in 1984 by an interdisciplinary group of high-flying scientists to foster theoretical research into complex systems. The 'complexity theory' paradigm pioneered by the Santa Fe Institute has led to some very elegant mathematical work, to a large volume of interesting publications and to the definition of a new field (artificial life), but has also been criticized as a rather hollow intellectual fad (Horgan 1995). Just how relevant is complexity theory to environmental modeling?

There is little doubt that the environmental sciences deal with systems that are very complex by any definition. Unpredictable outcomes, major consequences of relatively small disturbances, unanticipated side effects, the fragility of large environmental systems or, conversely, the robustness of others that appear very delicate, all provide empirical evidence of complex systems behavior. Examples of self-organization abound in the natural world: grains of sand forming crescent-shaped dunes; birds flying in triangular formations; surface runoff converging to a few discrete channels. Phillips (1999) distinguishes eleven distinct kinds of self-organization that are relevant to landscapes, which may be further aggregated into two broad categories: those that tend to create order and regularity in the landscape, and those that result in greater diversity and differentiation. On the other hand, outside physics and the laboratory, there are not that many empirical examples of some of the 'sexier' aspects of complex systems behavior (in particular chaos) in environmental systems. For example, the wide fluctuations of animal populations in landscapes were earlier seen as a striking case of chaos in action. But as Zimmer (1999) reports, citing a well-known ecologist, "there is no unequivocal evidence for the existence of chaotic dynamics in any natural population". Indeed natural systems are often found to totter 'on the brink on chaos' without quite plunging into it – a sign of Mother Nature's resiliency, if not wisdom, in the face of constant perturbations and assaults.

Very often the interesting dynamics of complex systems are the macro-scale outcomes of simple interactions among micro-level system components. Neural networks are well known examples of complex structures capable of highly organized behavior resulting from the parallel operation of large numbers of interconnected neurons. When the micro-level interactions are restricted to neighboring elements, the resulting system is intrinsically spatial and under appropriate conditions it will produce spatial organization at the macro-level: molecules in a solution yielding regular patterns on the surface of the liquid, pigment activators and inhibitors creating stripes or dots on animal skins, segregated neighborhoods unexpectedly arising from simple preferences of individuals for particular levels of racial mix among their immediate neighbors. Cellular automata (CA) are a well known class of complex systems models that embody that principle, generating macro-scale spatial patterns in a gridded space through the parallel operation of micro-scale rules involving local neighbors (Wolfram 1984; Wolfram 1986). CA models have become increasingly popular with environmental modelers because of their direct compatibility with raster GIS, their ability to make use of detailed spatial data, and their conceptual simplicity, which contrasts with the extreme diversity and complexity of the patterns they are capable of generating. CA models have proven equally suitable for the simulation of physical and social spatial processes, and are thus particularly well suited for integrated environmental modeling (White and Engelen 1997; Clarke and Gaydos 1998).

Agent-based simulation is a more recent development in complexity theory that also involves generating complex macro-scale behavior through modeling micro-scale interactions. 'Agents' are interacting entities that may be sentient (people, animals, organizations…) or non-sentient (any kind of physical or computational objects) and their interactions may or may not be in space. As in CA models (and unlike neural net models) interactions among agents can be based on arbitrarily complex rules. Unlike CA, where the interacting elements are localized cells, interacting agents may be mobile in space, thus providing a straightforward, intuitive way of modeling actually moving organisms or other objects. Applications are already appearing in the environmental modeling domain, such as the simulation of the impacts of visitors on wildland settings by Gimblett et al., (1999).

Critics of complexity theory point out that the wide variety of surprising behavior exhibited by mathematical and computational complex system models is rarely found in the empirical world. The criticism is primarily directed at the 'bottom up' paradigm which tends to produce especially skittish models, very sensitive to initial conditions and to small variations in the interaction rules. Real-world populations rarely crash and then explode chaotically, local interaction rules are rarely as simple as these models would have it, landscapes don't easily jump from one state of organization to the next, neither natural nor social systems tend to get into runaway positive feedback loops, and 'emergence' seems to be just what the current model cannot explain. In other words, there is much more stability in the real world than complexity theory would have us think. Some authors contrast 'model complexity' (or 'model chaos') to actual system complexity (Malanson 1999), and Goldenfeld (1999) warns researchers 'not to model bulldozers with quarks'. The issue here is that there is a right level or levels of description for every phenomenon that must be judiciously chosen for the model to work. This is one of the many lessons that modelers are learning from complexity theory. There are several other lessons: that nature can produce complex structures even in simple situations, and can obey simple principles even in complex situations; that each complex system is different so that similar-looking systems may develop in very different ways (Goldenfeld 1999). Even though we may never enjoy the intellectual comfort of scientific laws when modeling complex environmental systems, complexity theory has made us more aware of the subtlety, diversity, and interconnectedness of the phenomena we study, and has contributed many powerful concepts, modeling approaches and techniques.

4 *Environmental modeling and geocomputation: modeling 'with' the computer*

Modeling 'without' the computer is inconceivable in the environmental domain these days, except perhaps when developing abstract conceptual models. In many ways the computer has made environmental modeling possible, and not just because of computing in its original, number crunching sense. In this data-dominated age GIS has given modelers the possibility to handle arbitrarily detailed data at any spatial scale and is unquestionably a major driver behind the current blossoming of environmental analysis and modeling. Statistical, mathematical, graphics and visualization software has complemented the increasingly sophisticated capabilities of commercial GIS, providing additional power to modelers and literally new ways of looking at data. But modeling 'with' the computer means something more than that.

In section 2 computation was mentioned as a separate stage that is reached late in the development of a model, after the real modeling work has been completed. This view is less and less tenable as the computer increasingly becomes an integral component of the modeling of complex systems and processes instead of a tool for handling data and solving equations. More and more, computer simulation replaces analytic model development as the systems modeled become larger, more integrated and more complex. Step 2 of Smyth's (1998) sequence in particular, the formalization of the model's ontology, tends to be merged with step 3, the computational expression of the model. Formal languages such as Haskell and Gofer have been developed that are at the same time algebras and computer languages. Map algebra (Tomlin 1991) and image algebra (Ritter, Wilson, and Davidson 1990), which are formalisms operating on spatial elements as the variables, have been extended into dynamic spatial modeling languages such as PCRaster (Burrough 1998). In addition, graphical, icon-based model construction environments are attracting increasing attention (Maxwell and Costanza 1997) and in simple forms even begin to be available bundled with commercial GIS software (e.g., ESRI's ModelBuilder available with ArcView Spatial Analyst 2.0). More generally computer visualization has substituted the advanced pattern-recognizing capabilities of the human eye-brain system for much of the deductive work that characterizes traditional scientific analysis. All these developments aim at making environmental modeling easier, more widely available, and more of a collaborative enterprise than it could ever be under the traditional approach.

Just as the logical steps of model building are being compacted and merged, the distinction made in traditional model ontologies between entities, relationships, physics, and logic is becoming less and less sharp with the growing popularity of object-oriented languages and their recent extensions. In this approach objects are defined in terms of the possible and allowable behaviors of the corresponding real-world entities. Object-orientation, with its emphasis on representing quasi-autonomous units within models and submodels, facilitates a bottom-up approach to complex system modeling and especially favors agent-based simulation. Indeed, object-orientation has been loosely defined as "the software modeling and development disciplines that make it easy to construct complex systems out of individual components" (Khoshafian 1993). Further developments currently underway in Internet-oriented computer languages are likely to affect modeling practices even further. XML (Extended Markup Language) and its derivatives for example are considered especially well suited for sharing and handling geographic data over the Internet, opening up the possibility for environmental models that are not just dynamic, but are themselves dynamically evolving with the contributions of modelers 'anywhere, any time' (Lowe 2000).

Computation is thus taking a life of its own in environmental modeling, increasingly driving rather than just supporting modeling efforts. Some may view this as a regrettable development that threatens to distance environmental modeling from proper scientific practice – except that, of course, similar developments are taking place to a greater or lesser extent in practically all areas of science. Researchers in the spatial sciences are converging around the notion of *geocomputation*, a novel concept whose definition keeps evolving just as its subject matter does (Longley et al. 1998; Couclelis 1998a). Originally no more than a diverse grab-bag of computational techniques, geocomputation eventually came to be identified with GIS practice for some people, but now seems to have acquired an identity of its own as the convergence of computer science, geography, information science, mathematics and statistics. Once its theoretical potential is fully unfolded geocomputation may become synonymous with the computational theory of complex spatiotemporal processes (Couclelis 1998b). If that's the case environmental modeling will surely become geocomputation's proudest application field and may benefit immeasurably from a formal convergence of all the relevant technical fields.

5 Conclusion

These are heady days for environmental modeling. The talent and the money are there, we're drowning in environmental data, the growing wonders of geocomputation keep us on our toes, big problems await our wisdom for their solution, and the policy makers may for once be listening! There are things we already do very well, and there are things we will need to do even better. Summing up such a vast, multi-faceted, fast moving field is too much of a challenge for any single person to undertake, but here are some points to take home from the discussion in this chapter.

First, environmental modeling is primarily an applied field addressing problems that are directly or indirectly of considerable societal importance. Environmental models need to be policy-relevant. This does not mean that we are expected to build 'answer machines' but rather, that our models must be good enough to be taken seriously in the policy process. Speaking from experience King and Kraemer (1993), p. 356) list three roles a model must play in a policy context: A model should clarify the issues in a debate; it must be able to enforce a discipline of analysis and discourse among stakeholders; and it must provide an interesting form of 'advice', primarily in the form of what *not* to do -- since no politician in his or her right mind will ever simply do what is suggested by a model. The properties a good policy model needs to have been known since the time of Lee (1973) and his 'requiem to large-scale models': transparency, robustness, reasonable data needs, appropriate spatio-temporal resolution, and the inclusion of enough key policy variables to allow for some of the really interesting policy questions to be explored.

Second, the fact that environmental modeling is primarily an applied field does not exonerate it from the need to be theoretically well grounded. It is all too easy to write and calibrate simulation models that do neat things on a computer screen but have an underlying ontology less plausible than that of a computer game. Since it is extremely unlikely that we will ever have a 'theory of everything' in the environmental domain we must get better at piecing together the wide array of partial theories (some highly respected and reliable, others very controversial and unreliable) contributed by the physical, biological, technological and social sub-fields of the environmental sciences. Integrated environmental modeling is more than a matter of opting for integrated rather than coupled models: rather, it has to do with making sure that the patchwork of concepts, ontologies, approaches, laws, rules of thumb, degrees of confidence and spatio-temporal structures that may come together within a single framework, respects the strengths and weaknesses of each part and yields a whole that logically hangs together (Couclelis and Liu 2000). Formal theories of modeling and someday soon perhaps a more mature science of geocomputation should provide the foundation for scientifically rigorous environmental models. These will help put back together the world we tried to understand by pulling it apart into smaller and smaller sub-disciplinary pieces, thus fulfilling von Bertalanffy's vision of science unified though system theory.

Citing King and Kraemer (1993) once again (who paraphrase Dickens), "the Spirit of Modeling produces the shadows of what Might be, only. No one knows what Will be." How true. Illuminating the shadows of what Might be is what environmental modeling is all about.

References

Alberti, M. 1999. Modeling the urban ecosystem: a conceptual framework. *Environment and Planning B* 26, no. 4: 605-30.

von Bertalanffy, Ludwig 1968. *General System Theory*.. Harmondsworth, Middlesex, England: Penguin Books Ltd.

Burrough, Peter A. 1998. Dynamic modelling and geocomputation. In *Geocomputation: a primer.* Eds. P. Longley, S. Brooks, B. Macmillan, and R. McDonnell, Ch.9. New York: Wiley.

Casti, John L. 1989. *Alternative Realities Mathematical Models of Nature and Man.* New York: John Wiley & Sons, Inc.

Casti, John L. 1997. *Would-be worlds: how simulation is changing the frontiers of science.* New York: John Wiley & Sons, Inc.

Clarke, Keith C., and Leonard J. Gaydos. 1998. Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and

Washington/Baltimore. *International Journal of Geographical Information Science* 12, no. 7: 699-714.

Couclelis, Helen. 1998. Geocomputation and space. *Environment and Planning B: Planning and Design* , no. 25th Anniversary Issue: 41-47.

Couclelis, Helen 1998. Geocomputation in context. In *GeoComputation: a primer*. Editors Paul Longley, Susan Brooks, Rachael McDonnell, and Bill Macmillan, 17-29. New York: Wiley.

Couclelis, Helen and Xiaohang Liu 2000. The geography of time and ignorance: dynamics and uncertainty in integrated urban-environmental process models. In *Proceedings, GIS/EM4 Conference*: www.Colorado.edu/research/cires/Banff/upload/136.

Egenhofer, Max J., and Reginald G. Golledge. 1998. *Spatial and temporal reasoning in geographic information systems*. New York: Oxford University Press.

Forrester, Jay W. 1975. *Collected papers of Jay W. Forrester*. Cambridge, Mass.: Wright-Allen Press.

Gimblett, H. Randy, Merton T. Richards, and Robert M. Itami. 1999. A complex systems approach to simulating human behaviour using synthetic landscapes. *Complexity International* 6, no. January.

Goldenfeld, Nigel and Kadanoff Leo P. 1999. Simple lessons from complexity. *Science* 284, no. 2 April: 87-89.

Horgan, John. 1995. From complexity to perplexity: can science achieve a unified theory of complex systems? *Scientific American*, June: 104-9.

Khoshafian, S. 1993. *Object-oriented databases*. New York: John Wiley.

King, John Leslie, and Kenneth L. Kraemer. 1993. Models, facts, and the policy process: the political ecology of estimated truth. In *Environmental modeling with GIS*. Eds. Michael F. Goodchild, Bradley O. Parks, and Louis T. Steyaert, 353-60. New York: Oxford University Press.

Lee, Jr Douglass B. 1973. Requiem for Large-Scale Models. *AIP Journal* May 1973: 163-77.

Longley, Paul A., Sue M. Brooks, Rachael McDonnell, and Bill Macmillan. 1998. *Geocomputation: a primer*. Chichester: Wiley.

Lowe, Jonathan L. 2000. What the XML are scalable vector graphics? *Geo Info Systems* , no. May: 46-50.

Maxwell, T., and R. Costanza. 1997. A language for modular spatio-temporal simulation.

Ecological Modeling 103, no. 2-3: 105-13.

Odum, Howard T., and Elisabeth C. Odum. 2000. *Modeling for all scales: an introduction to system simulation*. New York: Academic Press.

Ritter, G. X., J. N. Wilson, and J. L. Davidson. 1990. Image Algebra: An Overview. *Computer Vision, Graphics and Image Processing* 49: 297-331.

Smyth, C. Stephen. 1998. A representational framework for geographic modeling . In *Spatial and temporal reasoning in geographic information systems*. Eds. Max J. Egenhofer, and Reginald G. Golledge, 191-213. New York: Oxford University Press.

Tomlin, C. D. 1990. *Geographic Information Systems and Cartographic Modeling*. Englewood Cliffs, NJ: Prentice Hall.

Waldrop, Mitchell M. 1992. *Complexity the Emerging Science at the Edge of Order and Chaos.*. New York: Simon & Schuster.

White, R., and G. Engelen. 1997. Cellular automata as the basis of integrated dynamic regional modelling. *Environment and Planning B: Planning and Design* 24, no. 2: 235-46.

White, Roger, and Guy Engelen. 1999. High resolution integrated moidelling of the spatial dynamics of urban and regional sytems. HC.

Wilson, A. G. 1981. *Geography and the Environment Systems Analytical Methods.* Chichester: John Wiley & Sons, Ltd.

Wolfram, Stephen. 1984. Cellular automata as models of complexity. *Nature* 311, no. 4: 419-24.

Wolfram, Stephen 1986. *Theory and Application of Cellular Automata*, Singapore: World Scientific Publishing Co.

Worboys, Michael F. 1995. *GIS: a computing perspective.*. London: Taylor & Francis.

Zeigler, Bernard P. and Tag Gon Kim 2000. *Theory of Modeling and Simulation: Integrating Discrete Event and Continuous Complex Dynamic Systems*. 2d edition. New York: Academic Press.

Zimmer, Carl. 1999. Life after chaos. *Science* 284 (5411), no. 2 April: 83-86.