
Landscape Models and Explanation in Landscape Ecology— A Space for Generative Landscape Science?

Daniel G. Brown

University of Michigan

Richard Aspinall

Macaulay Institute

David A. Bennett

University of Iowa

Further development of process-based spatial models is needed to facilitate explanation in landscape ecology. We discuss the dual modeling goals of prediction and explanation and identify challenges faced in explaining landscape patterns. These challenges are especially acute in attempts to explain patterns that result from complex adaptive systems. We compare examples of two process models used to describe landscape changes in Yellowstone National Park as a consequence of predator-prey interactions. Generative landscape science is offered as a complementary approach to explanation, combining models of candidate processes that are believed to give rise to observed patterns with empirical observations. **Key Words:** complex systems, spatial modeling, spatial pattern.

A central theoretical concern in landscape ecology is understanding the interaction between observed landscape patterns and a diverse set of social and environmental processes. The domain of landscape ecology in the United States has been defined, primarily, around the causes and consequences of spatial pattern, expressed primarily in terms of biotic and abiotic processes (Naveh 1982; Risser, Karr, and Forman 1984; Turner 1989; Nassauer 1995; Mladenoff and Baker 1999; Turner, Gardner, and O'Neill 2001). Although Turner, Gardner, and O'Neill (2001, 7) "do not think it necessary to include a human component explicitly in the definition of landscape ecology," we take a more inclusive view, derived from the European origins of landscape ecology (Naveh 1982), that concerns itself not just with the interaction of landscape pattern with biophysical processes, but also with human actions. This view would seem essential to any attempts to make claims about the implications and/or appropriateness of management interventions, and to contribute to the emerging "integrated land science" described by Klepeis and Turner (2001). Models of landscape change have been used extensively to

study the effects of both natural and human processes on landscape patterns since the emergence of landscape ecology in the United States during the 1980s (Baker 1989).

An important thread of work in geographic information science (GIScience) deals with spatial models that can formally represent patterns and processes (e.g., Goodchild, Parks, and Steyaert 1993). Pattern-based models focus on describing spatial distributions and identifying correlates of those distributions (e.g., Guisan and Zimmermann 2000), whereas process-based models describe process using a number of different representations of mechanisms. Among the variety of purposes for which landscape models are built, two are most important in driving the nature and structure of models: (1) to make inferences about how and why landscapes change, sometimes (not always) with the intent to produce more favorable outcomes, and (2) to predict future landscape states and patterns. These two goals are difficult to separate from one another. On the one hand, we can hardly expect to make reasonable predictions about future landscape patterns if we do not have reasonable explanations for how they

change. On the other hand, given a particular explanation, encoded in a model, we commonly use the model's predictive ability as the fundamental measure of its veracity.

Assuming that *science as science* is built on general explanations, we focus in this article on the use of process models in landscape ecology for building explanations of landscape patterns and dynamics. Parunak, Savit, and Riolo (1998) made a useful distinction between two forms of process models, both of which encode mechanisms: equation-based models and agent-based models (ABMs). In GIScience, equation-based models might be understood as a special class of models that describe the processes by which attributes change at locations, which we refer to here as *location-based models*. We provide examples of an equation-based model and an ABM from research on landscape change in Yellowstone National Park.

We hope to illustrate how the use of models for explanation in landscape science represents an important frontier. We believe there is an opening for further integration of GIScience and landscape ecology in the development of an approach to the science that we, borrowing from but also going beyond Epstein and Axtell (1996) and Epstein (1999), refer to as "generative landscape science." Generative science concerns itself with understanding how micro-level processes can generate macrophenomena (Epstein 1999). For a generative landscape science, the outcome or phenomenon of interest is typically spatial pattern, though some elements of the dynamics may be of interest, for example, a sudden surge of landscape change that lags some environmental or social change. Work is well underway in a number of quarters to develop the theory and tools required for this science in both landscape and urban studies (Manson 2001; D. C. Parker et al. 2003; Benenson and Torrens 2004; Laney 2004; Brown et al. 2005). Here we hope to identify how spatial modeling tools in GIScience contribute to a generative landscape science and how that science can contribute in the context of the largely empirical emphasis of much of landscape ecology (Malanson 1999).

The Challenges of Explanation

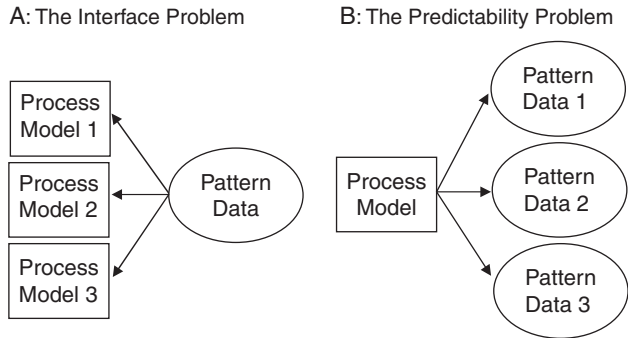
An important characteristic of a scientific explanation (i.e., Popper 1959; Salmon 1984) is

that it describes the process (the why or how) by which a phenomenon happens. In other words, it contains falsifiable cause and effect statements. Explanations are clearly distinct from empirical observations that describe patterns of a phenomenon, including its characteristics (what) and the locations (where) or times (when) it occurs. Models of process and observations of pattern, therefore, have complementary roles in landscape ecology. Though process models are important tools with which we can encode explanations, we contend that many of the models in landscape ecology and, especially, land cover change, are models of pattern, rather than of process. In pointing the way forward, we focus our discussion on models of process.

Some explanations are necessarily limited to particular places, others are generalizable concepts or processes that apply to a set of, or all, places. In the context of landscape change, processes and the relative importance of processes are variable from place to place, depending on the characteristics of the natural and human systems that exist at these locations. This issue brings to mind the discussions about the idiographic versus nomothetic nature of geography (Schaefer 1953). The nearest geography has to a general law, Tobler's first law of geography (Sui 2004), refers to pattern rather than process. It is a description of the general organization of space (i.e., near things are more related than distant things), rather than a statement about how or why space is organized in the way that it is. As a "law" it is intended to refer to all places rather than to a specific place.

We wish to highlight two important challenges in increasing our understanding through analysis of interactions between patterns and processes. The first is a well-known problem in spatial analysis that we refer to here as the *inference problem* (Figure 1A), which is that a given pattern (described through a finite number of dimensional metrics) can result from multiple processes (Fotheringham and Brunsdon 2004). For example, if we observe a fragmented pattern of forest (e.g., measured using statistics describing patch numbers and sizes), there is no *a priori* basis, without additional information, for concluding that the forest is fragmented because of the spatial pattern of logging or other disturbance activity or because it is growing in an area of patchy soil resources. Models that generate forest patterns through these two processes

Figure 1 Illustration of two fundamental problems of relating pattern and process in landscape ecology. Arrow direction indicates the reasoning process: **A** illustrates attempts to infer process from pattern; **B** illustrates attempts to generate pattern from process.



might both lead to statistically indistinguishable patterns of fragmentation.

We refer to the less commonly acknowledged inverse problem as the *predictability problem*, which is that a given process can produce multiple patterns (Figure 1B), especially where feedbacks and interactions produce complex adaptive systems (CAS; Holland 1995; Casti 1997). CAS, of the type referred to as aggregate complexity by Manson (2001), are characterized by aggregation, nonlinearity, flows, and diversity (Holland 1995; but see Malanson 1999 for a description of the relevance of these characteristics within biogeography). Reality produces only one observable pattern as a result of the process(es) at work in a given place and time. Yet, if feedbacks are present and/or the system exhibits path dependence and sensitive dependence on initial conditions, then the same processes could just as easily yield very different patterns under the same or similar boundary conditions (for a discussion of such processes in geomorphology, see Phillips 2004). Stochastic descriptions of process acknowledge variation in outcomes, but the variations resulting from CAS can be large and patterned in a way that requires process, rather than statistical, descriptions to characterize. When models have the characteristics of CAS, validating them against a single reality is not sufficient to conclude that the real process has been encoded or that any general process knowledge has been gained (Brown et al. 2005).

These problems are known and acknowledged to greater or lesser degrees in landscape ecology. The question we wish to explore is “how can new and existing methods of modeling from GIScience and elsewhere improve our ability to link pattern and process in landscape

ecology?” One possible answer is through the development and application of generative landscape science.

Process Models in Landscape Ecology

Landscape ecology has inherited an empirical emphasis from its parent disciplines of ecology, geography, and landscape architecture (Malanson 1999). Not surprisingly, then, many of the modeling approaches are data-driven (i.e., they are spatial models of pattern). A strong emphasis in much of this work is on the goal of predicting or forecasting landscape patterns in space and/or time, a goal that has gained urgency in the context of integrated global ecosystem sciences (Clark et al. 2001). Though empirically-based models are often built with the goal of explanation, the metric used to evaluate their quality is usually their ability to predict within or, preferably, outside of the sample used to estimate the parameters of the relationships. Reviewers usually insist on such a measure. The empirical emphasis of landscape modeling is also consistent with the relative paucity of theory; as Baker (1989, 127) noted, the “present limit to the development of better models of landscape change may be a lack of knowledge of how and why the landscape changes, and how to incorporate such knowledge in useful models.” Since that statement was published much progress has been made in the methodology to link land cover and land cover change to natural and social factors (see Lambin 1997; Mladenoff and Baker 1999; Guisan and Zimmermann 2000; Irwin and Geoghegan 2001; D. C. Parker et al. 2003). In most of this work there remains a reasonable tendency to focus on fitting observed landscape patterns and

on predictive accuracy as the primary measures of a model's veracity (Pontius 2002; Pontius, Shusas, and McEachern 2004). But to build our understanding of landscape systems, and explain the human and environmental drivers of change in those systems, landscape ecology can make better use of the power of additional approaches to spatial-process-based modeling that are being developed within GIScience.

What Dobson (1992) referred to as *process logic*, and contrasted with *spatial logic*, proceeds from our understanding, intuition, formal proofs, or guesses of how the world works to deductions about specific outcomes (i.e., patterns) that can be observed and tested in the world. Popper (1959) describes scientific investigation, in practice, as an alternating process of deduction (loosely related to process logic) and induction (in the case of geography, spatial logic). Computer simulation models of process within GIScience provide tools to bolster the iterative nature of this cycle in landscape ecology. Simulations have a longer history in physical geography than in human geography, though new tools are making it possible there as well (e.g., D. C. Parker et al. 2003; Benenson and Torrens 2004). The processes derived from our understanding are necessarily general in nature, though the relative importance of various factors or parameters can be adjusted (i.e., calibrated) to fit specific cases.

Scale is, of course, a matter of serious concern for geographers. One important scale issue involves the level of generality of that which we wish to explain or predict. In some instances, our goal relates to predicting specific outcomes at specific times and locations (e.g., will development happen in this place or another in ten years?). We would argue that because such predictions are specific, they are less suited to explanation in the general sense, and hence trying to achieve the goal of predicting finely grained patterns can conflict with the goal of general explanation. In a science of landscapes, scientific explanation should presumably occur at the level of the landscape (i.e., the *macrophenomenon*)—explaining why cities have particular patterns (e.g., sprawl), why landscapes get more/less fragmented over time, or why ecotones are abrupt or gradual. This approach mirrors “pattern-based modeling,” described recently by Grimm et al. (2005). These macrophenomena represent empirically observable structures that

might or might not have general or common causes. Spatiotemporal pattern characteristics, like those measured with landscape pattern metrics (LPMs) or temporal trajectories, can serve as indicators of such macrophenomena (D. Parker and Meretsky 2004). For example, Malanson and colleagues have used spatial models to identify how patterns at the alpine treeline ecotone might have formed as a result of environmental feedbacks (Bekker et al. 2001; Malanson 2001; Malanson, Xiao, and Alftine 2001; Alftine and Malanson 2004; Malanson, Zeng, and Walsh 2006).

A second scale issue relates to the spatial scale of representation, in this case representation of process. If we are to represent geographical landscape processes well, we need to be able to represent them at the scales at which these processes operate. Cause and effect representations that are applied to spatially aggregate phenomena clearly pose challenges for actually representing the mechanisms (the how or why) that cause many observed landscape relationships, as our understanding of the *ecological fallacy* cautions in statistical analysis (Robinson 1950). However, neither is it sufficient to always seek the finest level of disaggregation possible, because processes operate across scales and can, therefore, result in informative empirical relationships at multiple scales (Walsh et al. 1999). Similar issues of scale are of concern in our representations in the temporal dimension; that is, temporal patterns and cycles can be observed over varying time scales, and time intervals of observation need to sufficiently resolved to observe processes of various rates.

Location-Based Models

A whole generation of landscape simulation models has used locations on the landscape as their most fundamental representational unit, and usually represent the change process as a discrete event in which the landscape type changes at that location. These models often take the form of cellular models of discrete events of change, such as cellular automata, or of transition probabilities (e.g., Turner 1987; Baker 1989; Berry et al. 1996; Batty, Couclelis, and Eichen 1997; Lambin 1997; White and Engelen 1997; Clarke and Gaydos 1998; Brown et al. 2002). Such models can incorporate dynamics and feedbacks and, therefore, can represent CAS (Theobald and Hobbs 1998). However,

their utility for explanation can be limited by their sometimes nonintuitive relationship between the process as expressed in the model (i.e., through spatial factors that affect transitions or transition probabilities) and our intuition about landscape change (i.e., that it is carried out by organisms and actors that take actions and change landscapes). *Landscapes do not change spontaneously; they are changed by the action of organisms, human agents, and natural disturbance processes.*

Representing transitions as heuristic or probabilistic events can limit our ability to explain the mechanisms. For example, a statement of the form “forest clearing is more likely at locations that have better soil” may be consistent with observations, and the patterns simulated based on it may match observed patterns well, but why this relationship exists remains open to interpretation. Is it because these sites grow the types of trees that are in demand on the timber market, or because these sites are most desired for clearing, settlement, and agriculture? How can we adjudicate among alternative explanations? Of course, which process is ultimately the correct one has implications for implementing policies or management plans intended to achieve a particular landscape pattern.

One way to improve the level of explanation encoded in transition-based models is to use analytical equations that actually describe how the changes are made. So-called equation-based modeling is a specific case of location-based modeling that uses mathematical descriptions of processes, as opposed to fitted heuristic or stochastic representations. The following is a simplified example that illustrates how equation-based models of predator-prey processes can be represented spatially to describe vegetation change in Yellowstone National Park.

Example of an Equation-Based Model

In the wintertime, elk movements within Yellowstone National Park can be modeled as a balance between two competing objectives: maximizing net bioenergetic return and minimizing the risk of predation. Vegetation biomass on the landscape serves as forage for elk and is affected by foraging pressure, plant phenology, and snow conditions. The probability of elk death due to starvation is a function of this biomass and an elk's ability to efficiently find and consume forage. Likewise, the spatial

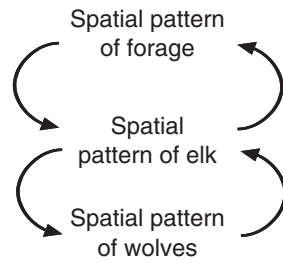


Figure 2 The spatiotemporal dynamics of forage, prey, and predator produces a complex adaptive system.

pattern of elk presents a resource to wolves. Elk prefer areas with high levels of forage and wolves prefer areas with high elk numbers. The landscape can, therefore, be conceptualized as two dynamic and interconnected potential surfaces: one pulling elk and wolves toward locations with high resource content, the other pushing elk away from locations that possess deep snow (rendering forage inaccessible) or high predation rates. The interconnectedness of these species, and the resulting spatial pattern of resources and risks, creates feedback processes that turn the landscape into a complex adaptive system (Figure 2).

The ideal free distribution (IFD) was proposed by Fretwell and Lucas (1970) to describe the optimal distribution of mobile consumers in relation to their food resources, and it was used to model landscape change within Yellowstone National Park as a function of these interactions. Farnsworth and Beecham (1997) have shown that the IFD is a limiting case of a more general model developed from diffusion relations; they give the general model as

$$\frac{v_i}{v_j} = \left(\frac{p_i}{p_j} \right)^{\frac{2\beta}{(1+2\delta\beta-\alpha-2\gamma)}}, \quad (1)$$

where v_i is the predator density in patch i , p_i is the prey density in patch i , α is a measure of departure from the IFD, β is a sensitivity parameter for the predator-prey relationship, δ is a measure of reward rate, and γ is a measure of decline in reward rate due to social aggregation (or predation).

Both the IFD and the generalized Farnsworth and Beacham model (the IFD models) assume that (1) habitat quality is distributed in homo-

geneous patches, (2) mobile organisms are omniscient and can switch between patches with negligible cost and in negligible time, (3) animals switch patches to maximize their fitness, and (4) fitness is positively related to habitat quality and negatively related to the density of others in a patch. The formulation and assumptions of these IFD models parallel the description and representation of environmental variability using object (vector) data types. Patches are represented in a spatial database as polygons, measures of habitat quality are represented as attributes of polygons, and the IFD models evaluate the relative pairwise merits of patches to allocate predators in the landscape. This representation, although matching the notation of the IFD models and the patch representation commonly used by landscape ecologists and found in vegetation maps, represents a static landscape pattern, even if the quality of patches varies between time steps, because the location and boundaries of patches typically cannot change through time in either the GIS or IFD models. The area between patches, the matrix, plays no part in the evaluation of patches. In essence, the IFD models implemented using a patch/polygon representation of environmental variability are a nonspatial type of model, albeit one that can produce a spatial representation of the relative quality of patches as a measure of fitness for predators.

An alternative implementation of this model can be developed using a field- (raster-) based representation of environmental variability (Lees 1996). This representation treats individual grid cells as the objects of interest. An additional modification to the model is to treat the various parameters of the model as functions of the local geographical neighborhood for each grid cell. Thus the reward rate (δ) and decline in reward rate due to social aggregation or predation (γ) are expressed as functions of the sum of the prey/habitat quality within distance w of each grid cell. Distance w can vary for δ and γ . For the example of elk and wolves, these distances may vary based on habitat type and the behavioral ecology of the species. Logistic functions for δ and γ are used in this example. These functions for δ and γ represent the spatial behavior of individual animals in relation to their resources and in response to their own and other species. The form of the functions can be constructed from field experiments or empirical

studies of animal spacing and resource use. This presents an opportunity for field landscape ecology to provide inputs on animal behavior to theory-based models, in this case a geographically-modified IFD model.

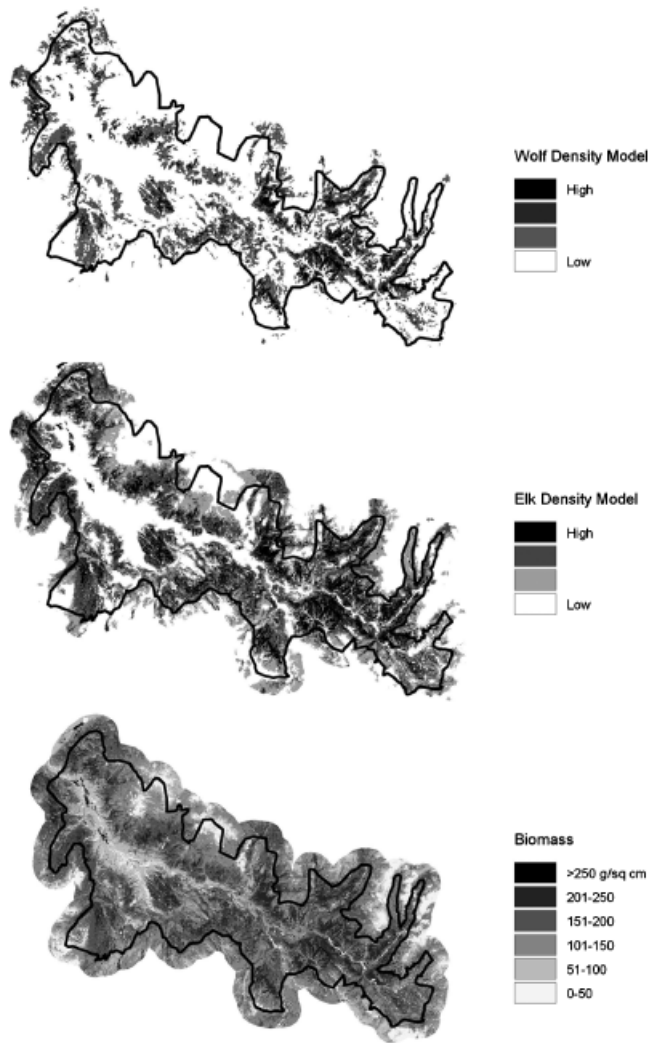
Solving the model (Equation [1]) for each pixel produces estimates for the distribution of elk and wolves at a particular time step (Figures 3A and 3B). The elk model is then used to update the biomass dataset and the models are again computed for the next time step (Figure 3C). Interactions between wolves and elk are thus explicitly represented in the model steps and can also be mapped at each time step or as a movie.

This approach has a number of advantages. First, the result is a temporally and spatially dynamic model of the interaction of environmental conditions, plant biomass, and elk and wolves, giving insight into the spatial and temporal dynamics of the system. Second, by using a raster representation of environmental heterogeneity, the model can be linked with other data, such as snow depth, that modifies the environment of the study area by relating the time step of the model to calendar time. Third, a variety of macrolevel outcomes can also be evaluated; these are of interest in their own right and may also help to validate the model (Bart 1995). For example, model outputs of interest might include density of animals integrated over time for specific patches, population distributions in different parts of the study area at different times, or potential impacts on vegetation based on modeled densities of elk in different parts of the study area summed over the winter. Finally, the model outputs can be evaluated with all available field data since they have not used any field data in their development; this avoids the confounding of training and validation datasets that can pose problems for pattern-based models.

Agent-Based Models

The recent development of individual-based models (IBMs) and ABMs (DeAngelis and Gross 1992; D. C. Parker et al. 2003) represents an opportunity to improve on the process representations enabled by equation-based models of locations. Individuals or agents can include organisms, people, households, collectives, institutions, and the like. By representing the behavior of each individual or agent, these models can characterize the separate effects of each at the appropriate scales and

Figure 3 Distributions, after ten time steps in the ideal free distribution model, of (A) wolf density, (B) elk density, and (C) biomass for the Northern Range of Yellowstone Park.



simultaneously represent the interactions between them, for the behavior of one agent in a model affects the state or behavior of another. IBMs for generating landscape patterns, for example, track the growth of individual trees or distributions of trees (He, Mladenoff, and Crow 1999; Prentice and Leemans 1990) and the response of mobile organisms, including elk (Bian 2003), to the environment (Westervelt and Hopkins 1999). ABMs include models of farmers making decisions about crop types and management techniques (Berger 2001; and Polhill, Gotts, and Law 2001; Balmann et al. 2002),

landowners making resource-allocation decisions (Evans et al. 2001), and home buyers making residential-location decisions (Benenson 2004; Brown et al. 2005). The following example illustrates the use of agent-based modeling to represent the same predator-prey interactions in the Yellowstone ecosystem.

Example of an Agent-Based Model

Although location-based models, like the IFD-based model described above, necessarily make assumptions concerning, for example, elk and wolf omniscience and their ability to compute

optimal strategies, these assumptions may limit the ability of the model to accurately reflect the processes by which elk and wolves learn about and adapt to a continually changing environment. Evolution may lead to near-optimal behavior at the aggregate level, but it does not produce individual elk with the cognitive ability to deduce optimal routes. Instead, elk act on bounded situational and spatial knowledge and uncertain information to navigate through complex landscapes during winter migration (Boyce 1989). Situational knowledge is a learned response to a perceived stimulus. Research suggests, for example, that an elk's migratory decisions (actions) are largely driven by snow depth (K. L. Parker, Robbins, and Hanley 1984; Sweeney and Sweeney 1984; Boyce 1989; Turner et al. 1994), perceived risks and resources (stimuli), and past experience (Boyce 1989; Ripple et al. 2001; Creel and Winnie 2005; Fortin et al. 2005). Agent-based modeling, therefore, complements the explanations provided by equation-based techniques by providing a mechanism by which individual-level behaviors can be explored.

Situational and spatial knowledge was incorporated into an ABM of elk/wolf interaction to simulate the spatial behavior of elk during their winter migration on Yellowstone's Northern Elk Winter Range (NEWR). In ongoing research, machine-learning algorithms, specifically evolutionary- and reinforcement-learning algorithms, are used by elk agents to learn *when to begin migrating* in response to snow depth and *where to migrate* in response to the spatial pattern of risks and resources. Situational knowledge is represented as action/stimulus couplets stored in a decision matrix. When-to-migrate knowledge, for example, is modeled as a decision matrix driven by the change in snow depth from one time step to the next. The values stored in the elements of this matrix record the probability of a migratory movement (the action) given a perceived change in snow depth (the stimulus). The learning algorithm attempts to maximize end-of-winter elk body mass.

Spatial knowledge builds as elk repeatedly interact with the environment and learn how to respond to the spatial distribution of positive (e.g., high availability forage) and negative (e.g., high predation risk) stimuli. This stored knowledge leads to more efficient and less risky

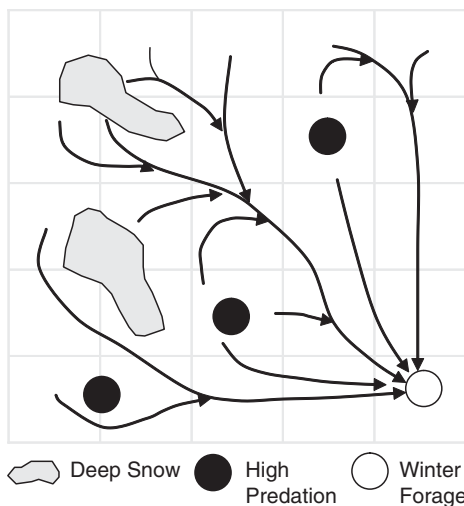


Figure 4 As elk navigate across a landscape they are attracted by resources (e.g., available forage and escape habitat) and repulsed by risks (deep snow and predation).

migratory decisions. Elk are attracted to certain locations, represented using a directed graph (Trullier and Meyer 2000). They are attracted to areas associated with positive stimuli (e.g., areas that typically possess high biomass), and repulsed from those associated with negative stimuli (e.g., areas that typically possess deep snow; Figure 4). The objective of the learning algorithms is to produce a cognitive map that stores the relative attractive and repulsive forces that exist on a landscape. These forces are stored as weights associated with each directed edge in the graph. Cognitive maps and decision matrices are modeled at the herd level to simulate the decision-making role of the lead elk in cow-calf herds. The results of this learning process are illustrated in Figure 5.

In the context of predator avoidance, elk can take one of three actions: forage as normal, become more vigilant and thus spend less time foraging, or flight. The stimuli include distance to wolves, distance to escape cover, and the health status of the elk. Situational memory is represented as a three-dimensional decision matrix (distance to escape habitat \times distance to wolves \times health status). Each cell in this matrix stores a 3-tuple, a string of three objects: here representing the relative importance

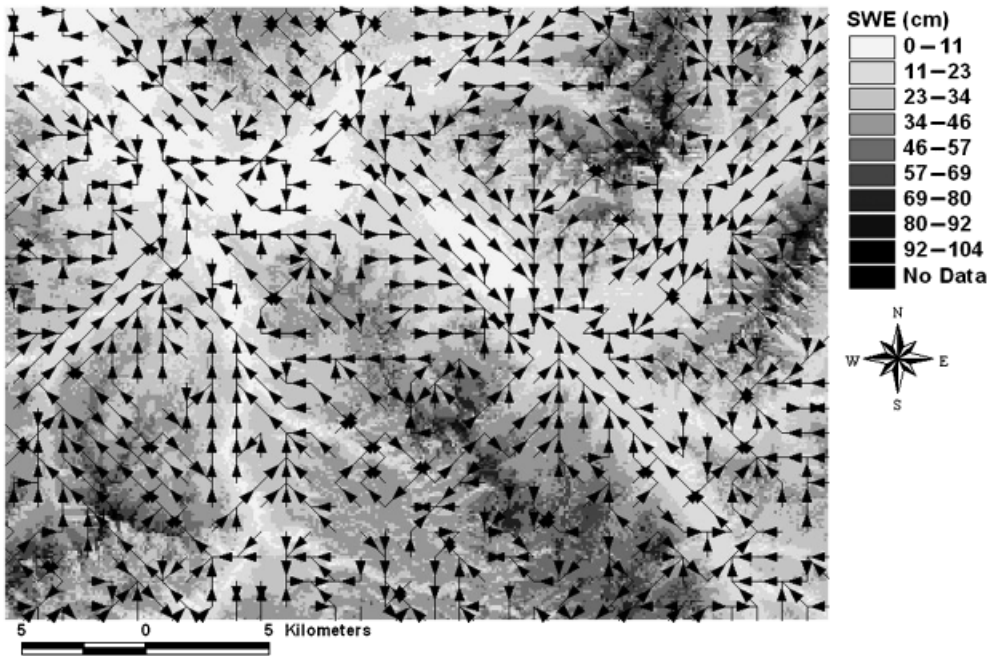


Figure 5 A cognitive map produced by the learning algorithm illustrating the most likely routes taken by elk to resource rich locations.

placed on foraging, maintaining vigilance, and flight given a specific combination of stimuli. Knowledge of the spatial pattern of risk is learned in a manner similar to the process described above. However, because wolves adapt to the changing spatial patterns of their prey, elk must also learn to ignore or forget old knowledge that is no longer supported by more recent observations.

ABMs like this one provide a means to explore (1) processes that drive individual-level behavior and interaction; (2) plausible hypotheses about how aggregate-level patterns emerge from individual-level behavior; (3) the impact that heterogeneity and random disturbance have on system outcomes; and (4) the consequences, expected and unexpected, of management decisions that are applied to CAS. These models are often inspired by, and therefore complement, the kinds of theories represented by equation-based simulations. However, many of the same characteristics that make ABMs useful also make them notoriously difficult to validate. It is not reasonable, for example, to expect that the migratory path of an individual

virtual elk will match the path taken by a real elk. This difficulty of prediction creates a challenge for generative landscape science.

Challenge of Generative Landscape Science

The goal of generative landscape science is explanation of landscape patterns—that is, to understand the processes and conditions that generate them (Grimm et al. 2005). The approach is to use computer simulations that represent the agents and behaviors that cause changes. Such methods, called *bottom-up* because they work with an atomistic view of the system to derive system-level outcomes (i.e., patterns), can have difficulty matching observed patterns as well as statistically fitted models, such as aggregate and averaged patterns of elk migration or household-level statistical relationships (e.g., Laney 2004) and processes (D. C. Parker et al. 2003). In a simple empirical test of scaling properties, Laney (2004) found that aggregation of land cover patterns

determined at the household level resulted in a poor match to observed patterns at larger scales. Jenerette and Wu (2001) developed a simulation to model land use change in central Arizona. Transition probabilities of the model were set in two different ways: first, based on average observed transition rates for cells with varying numbers of urban neighbors; and second, based on the outcome of a genetic algorithm that was trained to fit observed spatial pattern, measured through landscape pattern indices. Naturally, the model with optimized transition probabilities reproduced the landscape patterns substantially better than the nonoptimized pattern. These two examples illustrate that it is hard to match landscape-level patterns by simply aggregating patterns and processes from a finer level of understanding.

Like the urge to “teach to the test” in education, there is a strong urge to focus on models that maximize some measure that compares the model output with real-world observations (i.e., goodness of fit or prediction accuracy), sometimes at the expense of intuition, deduction, and encoding of processes (Batty and Torrens 2001). The urge to fit model parameters to data has a basis in scientific rigor and is sensible when the goal is prediction (or doing well on the test). It has led to novel methods to calibrate parameters and optimize fit to observed patterns through back-casting (e.g., Clarke and Gaydos 1998; Jenerette and Wu 2001). However, when we build models from the bottom up we need to acknowledge that we will not have all the data we need and that the systems themselves may simply be unpredictable. The insistence on predictive power at the microlevel as the only measure of the correctness of a model, therefore, may be misplaced and has a number of consequences. First, although the goal is to produce a reasonable representation of the *process* that produced the pattern, such fitting exercises focus instead on representation of the pattern itself. The logical problems associated with using goodness-of-fit measures to test the veracity of a model are described by Oreskes, Shrader-Frechette, and Belitz (1994), and include the inference-laden nature of data and the fact that the systems they represent are never closed systems, as is implied by such comparisons. Second, Brown et al. (2005) demonstrated, with a model of urban growth, how the urge to fit data in path-dependent systems can result in a

model that predicts the actual outcome *too frequently* (i.e., is overfit) because there is only one observation from the real process to compare against.

This leads us to an interesting issue: we may understand well the processes that operate on a landscape, but still be unable to make accurate predictions about the outcomes of those processes. In these instances the processes themselves are inherently unpredictable. Nonetheless, refining our understanding—for example, about the predictability of the process—is still an important and valuable activity.

The science of landscape ecology could benefit from greater integration of generative approaches that complement both the inductive and analytical-modeling approaches that are more common in landscape science. The methods, especially agent-based and individual-based modeling, are available. By encoding what we think we already know about processes operating on a landscape, or about landscape processes in general, and comparing the outcomes generated by those models with observations, we can learn more about complex landscape systems and identify avenues for further empirical or experimental investigation. Comparisons of insights derived from our empirical and inductive approaches with those derived from our deductive and process-based approaches holds particular promise.

We need new metrics for comparing models and empirical observations. There remains a key role for spatial analytical methods to defining the outcomes in question, and comparing aggregate outcomes (e.g., D. Parker and Meretsky 2004). Brown et al. (2005) propose new metrics for comparing model-produced patterns with the one observed (or reference) pattern. The metrics acknowledge, first, that a model can produce many (sometimes very different) outcomes. Separate analysis of regions that are variant or invariant in model outcomes can help identify how well the model matches a reference map (i.e., the one reality), as well as how predictable the system appears to be, based on the model. Grimm et al. (2005) argue that comparing many different patterns from the model (e.g., spatial landscape patterns, temporal trajectories, and health of a population) can provide much stronger support for a model or explanation. They suggest distinguishing between primary patterns—those that we seek

to explain—and secondary patterns—additional patterns in the world that our model output can be compared with for validation of its mechanisms.

A generative component to landscape science can help us to

- Develop and encode explanations that combine multiple scales. Because agents can act on patterns at different scales (e.g., households on parcels, developers on subdivisions, and local governments on jurisdictions), and because the outcome of interest is usually aggregate in nature (e.g., overall pattern), generative landscape science facilitates explanations that combine processes at multiple scales.
- Evaluate the implications of theory. Epstein (1999) refers to generative science as essentially “intuitionist”; that is, it derives its explanatory power from use of our intuition. Intuition is a reasonable starting place for theory development and scientific investigation, but as system behaviors get more and more complicated (e.g., within CAS) it is difficult to intuit the outcomes and, in many cases, our intuitions about the dynamics of CAS are misleading and biased by past experience, culture, and education. Understanding the implications of our intuitions, and training them in the face of such complexity, can be helped with the use of bottom-up models. One approach is to explore the solution space of the model—for example, by “sweeping” the values of the parameters in the vein of sensitivity analysis. Such analysis is akin to experiments in which we change the environments or behaviors of actors in our simulation model (i.e., experiments that are impossible to do in the real world). For example, Schelling (1978) taught us that agents with a surprisingly low level of desire for neighbors like themselves produces a segregated settlement pattern.
- Identify and structure needs for empirical investigation. The modeling advocated here is intended as a complement to, not a replacement for, empirical investigation. Data analysis and fieldwork are needed to identify patterns of interest and as a source of information about candidate

behaviors for individuals and agents. It is clear that empirical and experimental work is needed to evaluate the possible mechanisms causing feedbacks, and their relative strengths. Models provide a means to structure this empirical work within a conceptual framework and to evaluate the consequences of the findings.

- Deal with uncertainty. Though the GIScience and geostatistics literature provides much guidance on dealing with uncertainty in spatial data, Banks (2002) identifies a kind of uncertainty—“deep uncertainty”—that is not well-characterized by existing spatial modeling methods. In addition to uncertainty (or error) in data and parameters, deep uncertainty exists when there is uncertainty or disagreement in the model or model structure. Inadequate empirical support for, or the necessary simplification of, the behavioral processes in a model are sources of deep uncertainty. By simulating processes at a level close to that of our understanding of behavior (e.g., at the agent or individual level), we can substitute alternative assumptions or theories about behavior and evaluate the aggregate outcomes of alternative model (e.g., rational decision-making versus bounded rationality versus satisficing).

At a minimum, incorporating “experiments” based on models into our analysis of landscape patterns can lead to the identification of interesting phenomena at the system level (e.g., tipping points, fragmentation or fractal patterns, and path dependence) using systems that are simpler than, but representative of, the real world. Also, we can hope to begin to recognize when prediction may not be a reasonable goal. A more ambitious hope is that these models can be used to test, and even adjudicate between, multiple competing explanations, especially through interaction and coordination with data collection and experimentation.

Conclusions

We have outlined how the integration of spatial modeling approaches from GIScience contributes to our understanding of pattern-process

relationships in landscape ecology. In this sense, our arguments are aimed firmly at developing GIScience modeling in support of landscape ecology theory and explanation. In this sense, the representational tools of GIScience bring analytical power to the science of landscape ecology. The two examples we provide of representing elk-wolf-landscape interactions demonstrate how alternative process models can be implemented with GISystems, and illustrate the differences between location-based and ABMs. To fully exploit the promise of a tight integration of landscape pattern/process representations with hypothesis testing in landscape ecology, further work is needed both in the development and application of tightly coupled pattern-process representations within GIScience and in their exploitation for pattern-based analysis of landscape processes. Developments in both of these areas continue apace, and their simultaneous development offer significant promise to landscape ecology in being able to seriously address the mandate to understand how processes generate landscape patterns. ■

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- DANIEL G. BROWN is a Professor in the School of Natural Resources and the Environment, University of Michigan, Ann Arbor, MI 48109. E-mail: dan-brown@umich.edu. His research interests include linking observable landscape patterns, obtained through remote sensing, ecological mapping, and digital terrain analysis, with ecological and social processes.
- RICHARD ASPINALL is Chief Executive of the Macaulay Institute, Craigiebuckler, Aberdeen, AB15 8QH, United Kingdom. E-mail: r.aspinall@macaulay.ac.uk. This article was written during his tenure as Chair of the Department of Geography, Arizona State University, and as Professor of Geography in the Department of Earth Sciences, Montana State University. He is a member of the Science Steering Committee of the IHDP/IGBP Global Land Project, Editor of the Environmental Sciences section of the *Annals of the Association of American Geographers*, and Editor of the *Journal of Land Use Science*. His research interests are in land use, environmental geography, landscape ecology, GISystems and GIScience, remote sensing, and quantitative geography.
- DAVID A. BENNETT is an Associate Professor in the Department of Geography at the University of Iowa, Iowa City, IA 52240. E-mail: david-bennett@uiowa.edu. His research interests include GIScience and environmental decision making.