Chapter 20

Modelling and Simulation

George L.W. Perry

Introduction

Models and the practice of modelling have been the subject of ongoing debate in geography. Modelling 'has arguably become the most widespread and influential research practice in the discipline of geography, as indeed within the sciences more generally' (Demeritt and Wainwright, 2005, p. 206). The geographical literature is replete with reviews of various approaches to modelling and debates as to the merits, or otherwise, of modelling itself (e.g., see Macmillan, 1989b; Canham et al., 2003; Wainwright and Mulligan, 2004). In this chapter, I aim to provide a picture of the 'state-of-the-art' in the modelling of human-environment interactions, with a focus on simulation models and their evaluation. The focus is on the place of models and the nature of modelling as intellectual activities, rather than on the mechanics of model-building. The chapter is divided into two broad sections; the first focuses on current perspectives on modelling in geography and the second uses a series of case studies to illustrate how modelling is being practised.

Fundamental concerns for effective model-building and analysis are: (i) ensuring that the entity under investigation is appropriately represented and (ii) obtaining the data required to parameterise the models. These two issues relate to some of the crucial decisions of model-making: how detailed should a model be? How much causal (process) representation does it need to incorporate? At what scales in time and space should it operate? The problem of determining optimal model complexity, in terms of representational and empirical adequacy, is a recurrent theme of this chapter. A second underlying theme is that of complexity and complexity science (Medd, 2001; O'Sullivan, 2004). Over the last decade interest in and insights from 'complexity' and 'complexity science' have led to significant shifts in modelling socio-environmental systems. It is important to distinguish between complicated and complex systems. In complicated systems many components interact in a linear, or somehow predictable, manner (e.g., a multi-component, yet inherently predictable, system such as an aeroplane), whereas complex systems may comprise but few components, but (indirect) interactions between those components result in unexpected behaviours at the system-level (so-called 'emergence'). The central lesson of complexity science is that the dynamics of seemingly complex/complicated entities can be reproduced by simple models. In other words, complex problems do not necessarily require complicated answers[1]. That computer-based simulations are the main tool of complexity science has led to an examination of the place of simulation in science more generally and in particular to the question of 'where do simulation models lie in relation to theories and to experiments?' (see Humphreys, 1995/96; Dowling, 1999).

Approaches and Issues

What, why and how?

Models are idealised simplifications of some phenomenon or system. If modelling is nothing more than a process of simplified representation then nearly all conceptual activities might be described as modelling and verbal descriptions and cartographic maps could be called models. In this context, simplification entails paring back the representation of an entity until it contains only what is relevant to a given problem (a process often termed 'abstraction') as well as deliberate distortion to aid understanding (e.g., economists may assume perfectly rational decision making). As a result, models are *inherently* false and are known to be so. Thus, as the basic empiricist argument against scientific realism emphasises, considering a model to be 'true' is perilous (Morton, 1993; Oreskes et al., 1994; Beven, 2002). Nevertheless, and crucially, as Beven (2002) and Frigg and Hartmann (2006) point out, models may still be *approximately* true.

Given that all models are simplifications, one of their key traits is their level or degree of detail. This is usually thought of in terms of the number of parameters a model contains or processes it represents. As Batty and Torrens (2001) and Mulligan and Wainwright (2004) emphasise, parsimony is central to good modelling: we seek the simplest model that serves our purpose adequately. This does not mean that the absolutely simplest model is always the best solution; rather, we seek the simplest model that also serves the purpose we require of it. It is worth noting, however, that although modellers have tended to adopt this 'parsimony principle', observations of the 'real' world suggest that it is not simple, nor do simple answers seem consistently more useful than complicated ones. In practice, most (environmental) modellers tend to adopt what Beven (2002) terms 'pragmatic realism', that is they: (i) attempt to make their models as realistic as possible, and (ii) consider that even if current models are limited they will, over time, become ever more faithful mimics of the entity being represented.

Types of models

Methodologically, models are often classified as being conceptual, analytical (mathematical), empirical-statistical or simulation in form (table 20.1). Conceptual models are simply verbal, narrative or graphical descriptions of the system of interest, and the interactions and interdependencies between its components, while analytical (mathematical) models are distillations of conceptual models into the formalisms of mathematics. Empirical-statistical and simulation models are often distinguished by how they treat causality. Empirical-statistical models (e.g., regression approaches)

Table 20.1 A typology of modelling approaches

Model type	*Description*
Conceptual	Description of some system or process using narrative or graphical tools.
Analytical (mathematical)	Formal description of some system or process using the language of mathematics; can take many different forms including both deterministic and stochastic approaches. Note, however, that the term 'mathematical' is somewhat misleading as models almost invariably contain, to a greater or lesser degree, mathematical elements in some guise (Guisan and Zimmermann, 2000).
Empirical (statistical)	Models based on observed data (usually, but not necessarily, quantitative); includes statistical models.
Simulation	In a loose sense simulation simply involves 'building a likeness' (Kleindorfer et al., 1998). In general, however, it is usually taken to mean computer-based or *in silico* (see page 341) activity. Simulation modelling encompasses a multitude of activities ranging from the numerical solution of analytically intractable systems of equations to attempts to produce faithful *in silico* mimics or surrogates of specific 'real' world systems and processes (Winsberg, 2003; Küppers and Lenhard, 2005).

Note: Falling outside this typology are 'hardware' models, that is, scaled physical reconstructions such as flumes and wind tunnels.

are based on observations and focus on prediction of a system's dynamics; they do *not* consider why a change will occur, only what the nature of the change will be. Conversely, simulation models tend to consider the dynamics of the system and the processes that explain those dynamics; they consider what the response of the system might be to change and what processes explain that response. Thus, simulation models are often also referred to as 'mechanistic' or 'process-based' (Guisan and Zimmermann, 2000). In many cases the boundaries between the methodologies are blurred; for example, nearly all simulation models contain mathematical elements and some empirical component.

Another view is to consider models as being either 'top-down' or 'bottom-up' (Grimm, 1999). Bottom-up modelling is an atomistic approach, motivated by the belief that the dynamics and organisation of complex systems arise from, and can be explained by, interactions between the units that comprise that system. In environmental geography, agent-based models (ABMs) epitomise bottom-up modelling (Parker et al., 2003; Brown et al., 2004; Brown, 2006). In ABMs, the agents are autonomous, goal-seeking entities. Although agents often represent individuals, they may also represent aggregate structures such as family units, tribes, settlements or business organisations. Schelling's (1978) segregation model provides a famous example of a bottom-up, agent-based approach. In Schelling's model, householders are divided into two groups and have preferences regarding how many of each type of neighbour they prefer to live next to. 'Unhappy' households move to new sites in an effort to improve their situation. Over time the model produces broad-scale patterns of segregation, arising purely from decisions made by individual householders; macro-level patterns (segregation) 'emerge' from micro-level (individual) decisions.

By contrast, top-down modelling focuses on aggregate entities (e.g., entire populations) and on representing system-level relationships between aggregate variables with the goal of finding relationships between those variables. As such, it involves the application of general frameworks to particular problems (Grimm, 1999). The classical models of population dynamics, such as the exponential ($dN/dt = rN$) and logistic ($dN/dt = rN[1 - N/K]$) models, represent top-down approaches. These models assume that while all populations behave in the same general way, as is encoded in the functional form of the equation, the specific nature of their behaviour will vary from case to case, and this is specified by the exact parameter values used.

A final way to classify models is according to their use. Models serve three broad purposes in environmental geography: (i) predicting the future state of some system or phenomenon, (ii) making inferences about how a system or phenomenon is structured and changes, and (iii) integrating and synthesising knowledge and data from disparate sources. Bankes (1993) identifies two basic purposes of modelling:

1. *consolidation*: modelling based on compiling all available information about a system with the goal of creating a realistic and faithful surrogate of it. In this context prediction will be important, whether to test the realism of the model or to inform management and policy decisions about the actual system being modelled; and
2. *exploration*: modelling in the face of epistemic uncertainty, where the model is used experimentally to reduce this uncertainty by investigating the consequences of various assumptions about the modelled object. The goal of such modelling is heuristic.

This classification does *not* represent a rigid either-or division. Exploration and consolidation are synergistic. Improving our *understanding* of a process or system should enable us to predict its behaviour better (or determine whether it has the quality of predictability). Likewise, *reliable prediction* may lead to better understanding (Brown et al., 2006).

Consolidation: models for prediction

The desire to predict a system's or phenomenon's behaviour is a common motivation for modelling. Making predictions and testing them is central to the 'conventional' deductive-nomological model of scientific inquiry. Predictive models take many forms, from simple deterministic analytical models to complicated stochastic simulation models. In geography, predictive modelling is often equated with empirical-statistical models (e.g., regression models); indeed statistical modelling is probably the most commonly applied and most criticised form of modelling used by geographers (Macmillan, 1989a). As outlined above, empirical-statistical models are formalised descriptions based on observed characteristics of the entity of concern. While they may describe the links between components in a system, they do not consider the underlying mechanisms. This approach has often been denounced for yielding acausal and astructural 'black-boxes' that provide little heuristic insight (e.g., see Sayer, 1992).

Although empirical models are usually seen as focused strongly, if not solely, on prediction, they can also be used in an explanatory sense. The general intent of most empirical modelling is establishing a relationship between some variable x and a suite of predictor variables; establishing this relationship allows *indirect* causal relationships to be established (Mac Nally, 2000). Furthermore, there is increasing interest in applying statistical frameworks and tools, such as information-theoretic model selection and Bayesian statistics, to bridge the gap between exploration and prediction (Hobbs and Hilborn, 2006). In any case, the users of a prediction may be concerned solely with the reliability of the prediction. In such cases, a black-box approach may even be more appropriate than a complicated process-based model that explains the underlying processes responsible for driving the system being predicted (Demeritt and Wainwright, 2005). Furthermore, such models may also be suggestive of mechanism and help to generate new hypotheses.

Irrespective of how predictive modelling is best conducted there is, undoubtedly, a pressing need for reliable prediction to inform (environmental) public policy and decision making (Sarewitz et al., 1999; Clark et al., 2001; Pielke, Jr., 2003). Nevertheless, the goal of accurate prediction has, itself, been questioned. Clark et al. (2001, p. 657) take the pragmatic stance that '"Forecastable" ecosystem attributes are ones for which uncertainty can be reduced to the point where a forecast reports a useful amount of information'. However, Oreskes (2003) comments that the very factors that often lead us to modelling (limited understanding of/empirical information about a complex and/or complicated system) restrict the use of models for quantitative prediction. She argues that successful prediction in science has been limited to short duration, repetitive systems of low dimensionality, and that, even in such cases, successful prediction has often been reliant on trial and error. Conversely, socio-ecological systems may play themselves out over long durations, be non-repetitive, exhibit emergent or path-dependent behaviours, and be of high dimensionality – all traits that seem to preclude prediction (Batty and Torrens, 2001).

Unpredictability is also the key lesson of chaos theory. In chaotic (non-linearly deterministic) systems infinitesimally small differences in initial conditions will, in the long-term, result in completely different dynamics and system-states. These differences in initial conditions are much smaller than could ever be measured, and so, in a practical sense, chaotic systems do not even possess the quality of predictability (Gleick, 1987). Concerns over the ability to make reliable or meaningful predictions have, for example, been at the centre of the debate over the siting of the US high-level nuclear waste repository at Yucca Mountain, Nevada. 'Science', including, but not limited to, modelling, has played a central role in attempting to assess the performance of Yucca Mountain as a waste disposal site and billions of dollars (US) have been spent on this process (Ewing and Macfarlane, 2002). With a regulatory framework demanding safety assessments spanning tens of thousands of years (!), 'geoscientists in this project are challenged to make unprecedented predictions . . . ' in a context where epistemic uncertainty is high and the policy implications of those predictions even higher (Long and Ewing, 2004, p. 364). In such situations, where science and politics are intertwined and interdependent, there are important issues at stake about how the predictions scientists make are best interpreted and used (Macfarlane, 2003).

Exploration: models for learning

Besides prediction, models are vehicles for learning about the 'real' world. This is particularly true of simulation models. Recently, simulation models have become seen as systems that are open to examination in similar ways to other 'traditional' experimental systems (e.g., see Humphreys, 1995/96; Dowling, 1999; Winsberg, 2001; 2003; Peck, 2004). Certainly, the application of simulation modelling in some disciplines falls between traditional theorising and experimentation (Humphreys, 1995/96; Dowling, 1999). This approach opens up the possibility that following Dowling (1999), simulation models provide a means of 'experimenting on theories'. 'Experimental' simulation modelling seeks to mimic systems *in silico*[2]. The *in silico* form has the advantage that it can be manipulated in ways the 'real' world cannot; global climate change models are obvious examples of this (Frigg and Hartmann, 2006). Using models in this manner is a two-step process: we learn about the model and then transfer knowledge about the model to the target system. In practice, however, analysis often concentrates predominantly on the model. Nevertheless, it must be remembered that the model is a tool designed to help understand the real world; the (often understated) difficulty with detailed models is maintaining that connection (O'Sullivan, 2004; Frigg and Hartmann, 2006).

Models for integration: adaptive and participatory approaches

Models have become important tools for aiding in the decision-making process (e.g., forecasts of air quality are used to inform decisions about public health). Such modelling has often been viewed as the domain of the 'expert' and has been isolated from the rest of the decision-making process. Recently, this has begun to change as models are seen as integrative tools. Adaptive environmental management and assessment (AEMA) is an iterative process of structured learning through modelling, field experimentation and system monitoring (Walters, 1986). AEMA uses models to aid in the synthesis and integration of data and understanding, and to identify and reduce uncertainty. For example, Walters et al. (2000) used a series of conceptual and simulation models to filter various alternatives for restoring the flow regime affected by the Glen Canyon Dam in the Grand Canyon. Their models considered multiple spatio-temporal scales from localised algal responses to long-term patterns of sedimentation. They were used to: (i) highlight key areas of uncertainty in the system, and (ii) identify components of the system potentially amenable to controlled field experimentation. Model outcomes demonstrated the potential inability of the current monitoring framework to detect ecosystem responses to either experiment or management. Thus, models form(ed) part of an iterative and adaptive process, in which knowledge and understanding are constantly refined and management practices adapted to reflect this.

Models are also used to facilitate communication both between researchers in different disciplines and between the various stakeholders involved in environmental decision making. Castella et al. (2005) provide an interesting example of this approach. Castella et al. used a range of tools including a narrative model, an ABM, a role-playing game (derived from the ABM) and a GIS in an attempt to understand human-environment interactions and LUCC following Vietnam's *doi mois* economic reforms of the 1980s. The ABM explicitly considered: (i) farmers' decision-making strategies, (ii) the institutions that control resource use and access, and (iii) the dynamics of the biophysical and socio-economic components of the system. LUCC scenarios were developed with local land users using the role-playing game and the model, and were refined by repeated interactions between the researchers and the land users. The role-playing game helped the researchers to improve their understanding of farmers' decision making and how the actors deal with the risks engendered by uncertainty; it built trust and facilitated communication, and hence, model development.

Evaluating models: confrontation and experimentation

Verification and validation of models are much contested issues. Verification focuses on assessment of a model's structure (i.e., is the model free of logical, mathematical or coding errors?), whereas validation addresses on how exactly a model reproduces observed system dynamics (i.e., a model's predictions are confronted with observational data to assess its empirical adequacy). While some researchers believe that validation is central to modelling, others have argued that it is a logical impossibility (see Rykiel, 1996). Both verification and validation are, in essence, concerned with evaluating a model's adequacy against some criteria; what is 'adequate' will vary with a model's purpose. I will use the term 'evaluation' to encompass this broad(er) range of processes.

Models and their outcomes can be evaluated in many ways (table 20.2; Gardner and Urban (2003)). Kleindorfer et al. (1998) distinguishes objectivist, or founda-

Table 20.2 Some common methods of model evaluation and analysis, and their purpose

Method	*Description and purpose*
Structural	– Error propagation: Analysis of error in model output(s) as a function of the uncertainty associated with each parameter input to the model. – Sensitivity analysis: Identification of components of a model most sensitive to uncertainty and error in parameterisation.
Confrontational	– Visual 'diagnostics': Visual comparison of empirical observations and model predictions (i.e. by graphs). – Visual inspection for systematic bias, etc. – Statistical methods: Summary of differences between observations and predictions. – Quantitative comparison of predictions and observations (via correlation, regression and residual analysis, *t*-tests, difference measures, etc.). – Assessment of spatio-temporal trends in model performance and error.
Experimental	– Pattern-oriented modelling: Use of multiple observed patterns to evaluate and refine models and select between alternate representations (this will include structural and confirmatory evaluation). – 'Social' validation: Accepting a model as legitimate on the basis of consensus that it is valid by its users (this may or may not include structural and confirmatory evaluation).

Note: These methods are not mutually exclusive and most models are evaluated using a combination of the three.

tionalist, approaches to model evaluation from relativist and anti-foundationalist approaches. 'Classical' objectivist approaches to model analysis hinge on the 'confrontation' of a model with data, with the aim of establishing resemblance between the model's predictions and observations of the 'real' world; they emphasise the empirical verification of models and their outcomes. The tools used for establishing resemblance include graphical and visual diagnostics (e.g., time-series, residuals plots) and statistical (e.g., correlation and regression analyses, *t*-tests, summary difference measures) analyses (Mayer and Butler, 1993). Confrontational evaluation tends to emphasise an 'either-or' perspective: either the model and the predictions it generates are unambiguously valid, or they are rejected as unambiguously indefensible, with little in-between (Oreskes et al., 1994; Kleindorfer et al., 1998).

Contemporary philosophy of science emphasises several problems with the objectivist view that there is any unambiguous and impartial foundation for evaluating models and theories through some kind of self-evident and unproblematic confrontation with empirical data (Kleindorfer et al., 1998). First, recent discussions of model evaluation focus on the problems in seeing a model as 'true' (Rykiel, 1996; Oreskes, 1998; Brown et al., 2006). But second, even those embracing the idea of falsification as an alternative to the idea of validation must confront the problem of underdetermination. Observational data, it is argued, do not provide unambiguous grounds for evaluating theories as infinitely many hypotheses *might* explain a given dataset, even if only a small subset of these are actually plausible. This means that just because a model's predictions match empirical observations to some acceptable level, a model *cannot* be deemed either 'true' or 'correct'. A subset of the underdetermination problem is equifinality where there may be 'multiple model representations that provide acceptable simulations for any environmental system' (Beven, 2002, p. 2417). Finally, even the observed data used in the validation process carry assumptions, and so their place as a unique or truthful description of a system or phenomenon is itself questionable (Oreskes et al., 1994; Kleindorfer et al., 1998).

Even if their truth cannot be demonstrated incontrovertibly, models do have utility for elucidating how a system 'works' and for isolating where epistemic uncertainty is highest. Thus, and in keeping with a more exploratory approach to modelling, alternative modes of model evaluation have been developed, which tend to focus on what has been learned rather than on assessing the degree to which observations match model predictions. The adoption of more experimental approaches towards simulation modelling is premised on the belief that if models are experiments they should be evaluated as such (Dowling, 1999; Peck, 2004). One such approach is pattern-oriented modelling (POM – Wiegand et al., 2003; Grimm et al., 2005). POM involves the use of multiple observed spatio-temporal patterns with the aim of optimising model structure (by identifying components of the model central to aspects of observed behaviour), reducing parameter uncertainty, and testing and exploring alternate model representations (Grimm et al., 2005). Another more experimental approach is what Castella et al. (2005) call 'social validation' in which a model's users collectively agree that a model is a legitimate representation of the system (cf. Küppers and Lenhard, 2005); again, this is very different from the traditional emphasis on resemblance between observations and predictions. Castella et al. argue that social validation is crucial in participatory modelling, stating (p. 27) 'a model can only be used as a mediating tool for concerted action once it has been perfectly understood and is considered by decision makers to be legitimate'; this echoes Kleindorfer et al. (1998) who argue that model validation should be an open process involving model builder(s) and other stakeholders. Evaluating models in this way represents a significant departure from the objectivist methods typically used in the natural sciences. Development of alternative ways to evaluate models of all types remains fertile, if contested, ground.

Case Studies: Land-Use and Cover Change (LUCC)

Modelling LUCC is of active interest across geography and many other disciplines[3]. To illustrate the points raised in previous sections, I will consider some of the approaches taken to modelling LUCC. I do not intended to provide an exhaustive overview of activity in the field, but rather to provide an overview of the types of approaches that have been adopted. I will consider models in terms of the typology introduced in table 20.1, with the *caveat* that models typically span multiple of these categories; for example, simulation models usually contain analytical and empirical-statistical components. Finally, although LUCC is an obvious example of socio-ecological modelling, there are many other areas of environmental geography where models are routinely applied, including urban planning, climate change and its implications, resource models of water use and agricultural production, transport planning, reconstruction of palæo-environments, and prediction of the distribution of species and ecological communities (past, present and future), among other applications. The chapters in Wainwright and Mulligan (2004) provide a number of examples of specific modelling applications across the broad field of environmental geography.

Analytical models

Analytical models of LUCC focus on changes in the abundance of different land uses or conditions (e.g., economic values). These 'distributional models' (*sensu* Baker, 1989) are non-spatial and focus on how much change is taking place rather than where change is occurring. Transition (Markov) matrices are a commonly used type of distributional model. In Markov models, locations in the landscape are classified as being in one of n discrete categories. Repeatedly multiplying a $n \times n$ matrix, which describes the probability of transitions between each category, by a vector, which contains the abundance of each category in the landscape, results in a projection of change in the abundance of the various categories present in the landscape into the future under various restrictive assumptions. This approach has often been used in modelling LUCC (e.g., Turner, 1987; Hall et al., 1991; Romero-Calcerrada and Perry, 2004) because it is intuitive, conceptually simple and relatively easily parameterised (e.g., via time-series of remotely sensed imagery). However, in their simplest form, Markov models assume stationarity (constant rates of change in space and time) and ignore spatial neighbourhood effects.

A discipline where analytical modelling of land-use change has been much applied is economics. I will consider this economic framework here as much contemporary simulation modelling of LUCC (especially the agent-based approach) has been developed as a *reaction* to the microeconomic approach and its assumptions. The standard economic approach to land-use change is the 'bid-rent model' in which parcels of land (characterised by their location and other attributes) are allocated to the use earning the highest rent. This framework, based on rational utility theory, was originally developed by von Thünen for urban areas where property owners seek to optimise their location by trading off access to the urban centre with land rents. The model is equilibrial and spatially homogeneous, and (perhaps unsurprisingly) fails to reproduce observed patterns of city growth adequately; instead it produces concentric rings reflecting the balance between land value and transportation costs (Bockstael, 1996; Irwin and Geoghegan, 2001; Brown, 2006).

A few recent microeconomic models have departed from some of these restrictive assumptions and have adopted a spatially explicit perspective. For example, Bockstael (1996) and Irwin and Geoghegan (2001) describe a spatially explicit model of the economics of land-use conversion in the Patuxent watershed in northeast Maryland, USA. This region is a heterogeneous mix of rural and urban land uses and is undergoing rapid urbanisation, precisely the type of situation that confounds non-spatial bid-rent models. In Bockstael's model, land owners make decisions about whether or not to change land use at a given site on the basis of the future stream of returns to the parcel given how it is currently used (taking into account conversion costs). Because knowledge surrounding these decisions is imperfect, this decision-making process is framed as discrete probability choices. If there are n categories of land use, then there are n^2 decisions that land owners could potentially make. Bockstael (1996) reduces this to just one choice: whether or not to convert a land parcel from being undeveloped to developed. Thus, the model requires two pieces of empirical information: (i) the value of each parcel of land under any possible uses and (ii) the probability of conversion given those land values and associated conversion costs. To estimate these, Bockstael used an empirical model of land values (what economists term a 'hedonic pricing model') in which spatial factors such as neighbourhood conditions were included as drivers of land value, alongside more usual economic determinants of land value such as parcel size and access to transport infrastructure. The outcome of this model is a *static* map of probabilities of change. Using this framework, the implications of different public policy scenarios can be explored, as they influence the hedonic model, and the resultant probability maps compared. Subsequent extensions to the model (see Irwin and Geoghegan, 2001) made it temporally dynamic by incorporating a term that describes the optimal *timing* of the decision to convert land.

Although analytical approaches grounded in microeconomic theory have proven useful, they represent a different direction to that taken by geography and other disciplines (Drechsler et al., 2007). One of the key criticisms of such microeconomic models is the assumption that those involved in represent *Homo economicus* – the perfectly rational and informed decision maker. Furthermore, the emphasis in econometrics has largely been on temporal change and on equilibrial conditions (although spatial econometric tools are being developed – Irwin and Geoghegan, 2001). Again, these research directions are somewhat different to those taken in geography where the emphasis on space and disequilibrial conditions makes the use of analytical models problematic.

Empirical-statistical models

Empirical-statistical models, and in particular, a multitude of regression-derived approaches, have been widely applied for modelling LUCC. These regression approaches have been criticised on heuristic and methodological grounds; Brown et al. (2004, p. 401) identify some general problems with empirical-statistical models. First, statistical models of LUCC often assume that rates of change are stationary either in space or time or in both. Second, there are scale-related issues arising from the ecological fallacy and the modifiable area unit problem. Finally, the way in which change is represented is restricted by the limited way that relationships between predictor and dependent variables can be represented mathematically. In essence, the question to ask is 'how much can an empirical-statistical model illuminate process and causality?'

Millington et al. (2007) used empirical-statistical models in an effort to both understand and predict LUCC in the SPA 56 (central Spain). The SPA 56 is a heterogeneous and dynamic landscape comprising a range of land uses including agriculture, urban, peri-urban, recreation and forestry; it is designated a special protection area under the EU's 'Bird Directive' (Natura-2000 scheme). As in much of Mediterranean Europe this area has seen considerable land abandonment since the 1960s, largely driven by the decline of the traditional rural economy and rural-to-urban migration. Using satellite imagery, categorical maps and census information, Millington et al. (2007) derived statistical models of LUCC in the SPA 56. They employed multinomial logistic regression models, whose predictions were evaluated on the basis of pixel-by-pixel comparisons and by comparing the accuracy of the statistical models with a null model of zero change in the landscape (figure 20.1). The multinomial models suggested that the transformation of agricultural land to scrubland will continue into the future. Millington et al.'s predictive models

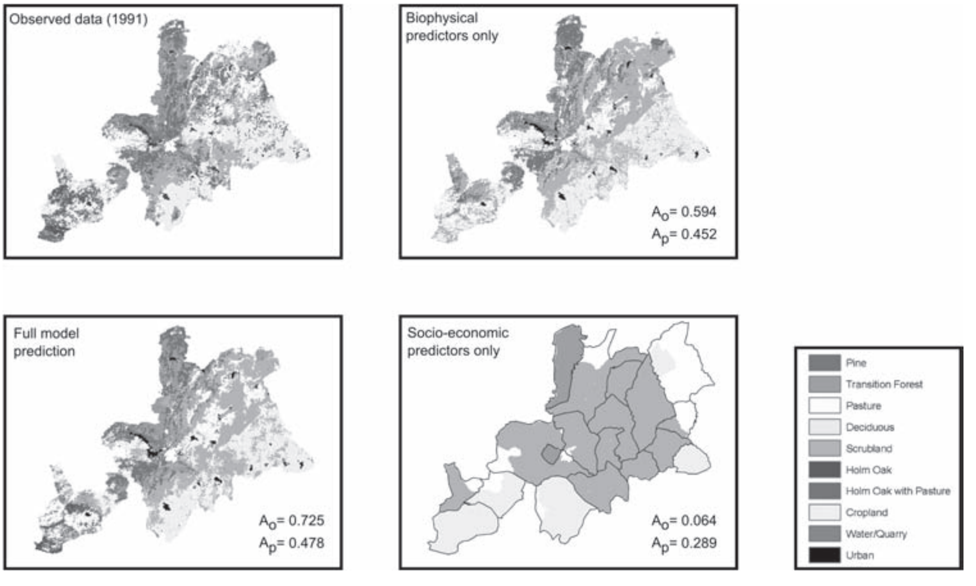

Figure 20.1 An example of confrontational-type model evaluation. Multinomial regression models containing different predictor sets (a full 'saturated' model, a model using only biophysical predictors and a model using only socio-economic predictors) were used to predict landscapes in the SPA-56, Central Spain. The predictions (for 1991) are compared with observed data (from 1991) on the basis of overall composition (A_o) and pixel-by-pixel (A_p) accuracy (proportional); analyses conducted by James Millington.

only perform better than the null model of no change over longer time periods, where they predicted approximately 70 percent of the landscape correctly on a pixel-by-pixel basis. Although they suggest how the landscape might change in the future should the *status quo* be maintained, these models epitomise the predictive 'black-box' approach frequently critiqued by geographers and others (e.g., Sayer, 1992; Mac Nally, 2000). Nevertheless, statistical tools are being developed that help explore relationships between a suite of predictor variables and the observed data. For example, hierarchical partitioning (used by Millington et al., 2007) estimates the contribution of each predictor to the total variance both in isolation and in conjunction with all other variables. Using such methods shifts the emphasis from producing the 'best' predictive model to isolating the variance explained by each predictor (Mac Nally, 2000). Such approaches are far better suited to hypothesis formulation than is the (often blind) search for the single 'best' predictive model.

Simulation models

Simulation models are used for prediction (e.g., forecasting of response to change using 'what if . . . ?' scenarios), synthesis and integration of data, and heuristic insight. They range in representational detail from very simple cellular-automata models to detailed agent-based representations of the decision-making process in spatio-temporally dynamic landscapes. There is a tension in simulation modelling of LUCC between models emphasising the ecological heterogeneity of the landscape at the expense of representing the actors engaged in decision making and *vice-versa*. This divide between landscape and actor has perhaps arisen due to the different foci of the various disciplines modelling LUCC (Veldkamp et al., 2001). In the social sciences the emphasis is on understanding the micro-level motivations of decision makers, whereas in ecology it is more on aggregate macro-level patterns of land use and habitat, with the hope that the socio-economic drivers of change are subsumed within the transition rules or probabilities. However, as Bockstael (1996) points out this means that the nature of these drivers is not transparent; public versus private and exogenous versus endogenous effects, for example, cannot easily be disentangled.

The two most widely adopted types of simulation model are grid-based and agent-based. Grid-based models (sometimes also called cellular or raster models) have been much used for spatial modelling of LUCC, especially, but not exclusively, by ecologists. In such models, the landscape is typically conceived of as a 2D $m \times n$ lattice, whose cells are internally homogeneous, with their state described by either a categorical (e.g., habitat type) or continuous (e.g., land value) variable. The cell size used will vary depending on the problem being addressed and may range from sub-meter (e.g., individual plants) to km+ (e.g., broadscale landscape pattern). Representations of change in grid-based models take a variety of forms including transition matrix approaches, simple quantitative neighbourhood rules, or more complicated hybrid semi-qualitative approaches (Perry and Enright, 2006).

Jenerette and Wu (2001) used a grid-based model to explore patterns of urban LUCC near Phoenix, Arizona. They employed a spatially explicit Markov approach in which transitions were a function of neighbourhood conditions. They developed models at two spatial grains: 250 × 250 m (coarse) and 75 × 75 m (fine). Jenerette and Wu used a parameterisation based on observed transitions and another one selected to optimise the models' fit to the observed data using genetic algorithms. Thus, Jenerette and Wu's predictions of urban change in the region combine statistical extrapolation with simulation modelling. Jenerette and Wu (2001) deemed the performance of the coarse-scale model over the period 1975–95 to be satisfactory. However, the fine-scale model did not perform as well, which Jenerette and Wu attributed to a mismatch in the scales at play in the system and in the model. Jenerette and Wu (2001) also experienced problems with the models' temporal (re)scaling. Estimation of the transitions between different land uses was based on observed data separated by a 20-year interval. These data had to be downscaled to annual transitions, but this downscaling failed when urbanisation was 'non-accretive' (i.e., occurred in entirely new parts of the landscape).

Agent-based models (ABMs) explicitly simulate interactions between autonomous goal-seeking entities, especially, in the case of LUCC, in some sort of dynamic landscape. Over the last decade ABMs have received increasing attention as tools for exploring human-environmental interactions and change (e.g., see Parker et al., 2003). One reason that they have been so eagerly adopted is dissatisfaction with the analytical rational-choice models traditionally used by economists. It has even been argued that bottom-up modelling (of which ABMs are a conspicuous component) represents a new 'generative' approach to social (Epstein, 1999) and landscape sciences (Brown et al., 2006).

An interesting use of ABMs of LUCC, in its broadest sense, is the reconstruction of human-environment interactions. One of the best known of such applications is the 'Artifical Anasazi' model. The Anasazi were a Puebloan (meso-American) group who occupied parts of the south-west of the USA. The Anasazi developed a rich culture in and around Long House Valley (NE Arizona) from about 1800 BC. before a rapid collapse triggered abandonment of these sites c.1300 AD. Detailed reconstructions of palæoecological and palæoclimatic conditions, based on dendrochronology and analysis of Packrat middens, have enabled estimates of annual maize production and hydrological dynamics, which have been used to parameterise the model. ABMs of this social system have been developed covering the period 300–1300 AD; in these models, the individual households are the agents (Dean et al., 2000; Axtell et al., 2002; Gumerman et al., 2003). The 'Artifical Anasazi' ABM follows the fate of individual families in the valley with households fissioning (as female agents age and marry) and moving in the landscape in response to water availability and food production. Early versions of the 'Artificial Anasazi' model (Dean et al., 2000) included few differences between individual actors and limited heterogeneity in the physical environment. Although this version of the model showed qualitative similarities to reconstructed population and settlement dynamics, quantitatively it was very different in that it predicted much larger populations and individual settlements than seems likely from the archæological record. More recent versions of the model (Axtell et al., 2002; Gumerman et al., 2003) incorporating more spatial heterogeneity in the landscape and variation in individual agent's characteristics provide a closer fit to the available data. In a spatial sense, the model now mirrors the known (from the archæological record) location of settlements, and it also mirrors, with one crucial exception, the expansion and rapid collapse of the population, in the face of deteriorating environmental conditions, in particular drought and changes in the water table (figure 20.2). The crucial exception is that the 'Artificial Anasazi' model predicts continued occupancy of the valley after it is believed that Long House Valley was completely abandoned. Thus, the modelling

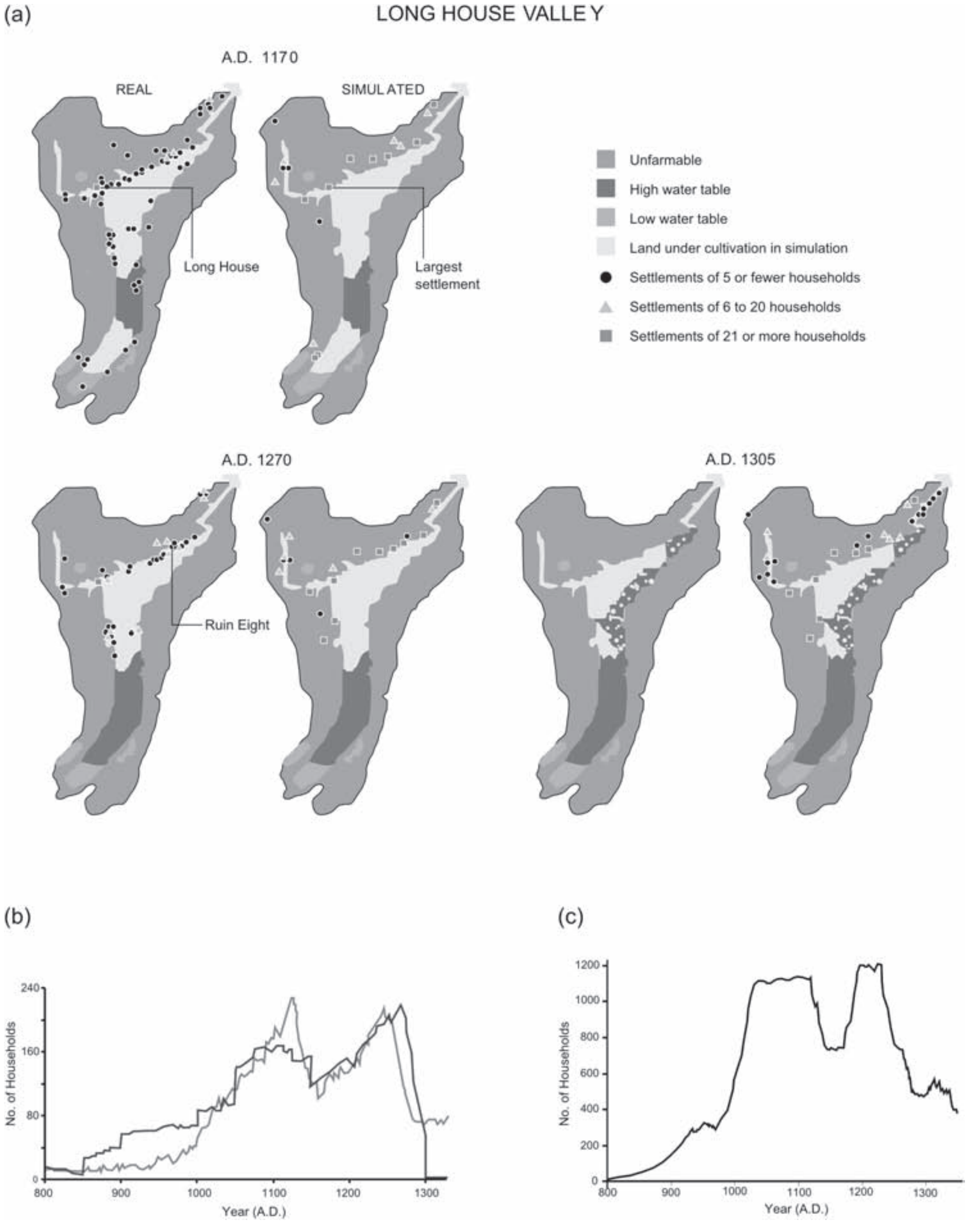

Figure 20.2 Evaluation of the Artificial Anasazi model: (a) comparison of landscape occupancy in the Artificial Anasazi model and as reconstructed from the archæological record; (b) time-series comparisons of number of households as observed (blue) and predicted (red) by the models of Axtell et al. (2002) and Gumerman et al. (2003); and (c) predictions of number of households in Long Valley in an earlier form of the model Dean et al. (2000) with limited spatial and inter-agent heterogeneity (note different *y*-axis scaling); figure drafted by Nicky Perry, (after Kohler, 2005). Original artwork by Lucy Reading-Ikkanda for Scientific American Magazine and reproduced with permission.

exercise suggests that although the environment may well have been the key control on the socio-environmental dynamics of this system, outside factors, such as longer-distance familial or other social ties, also influenced the Anasazi's behaviour, and may explain the total abandonment of the landscape that the model fails to predict.

Putting it all together

The examples discussed above lead to a series of questions about model representation and evaluation. All of the case studies are concerned with the broad question of what drives LUCC in some landscape, but the various models vary markedly in how they conceptualise and represent the landscape and the processes driving change in it. This variety suggests that there is not a single 'best' modelling approach. Rather some approaches will be more or less useful than others depending on the task at hand. Whatever their purpose, all models must wrestle with the challenges of balancing detail with parsimoniousness and determining the appropriate spatio-temporal scales to consider. In a now famous paper, Levins (1966) suggested that all model builders are forced to trade-off generality, precision, and realism. He believed that, at best, a single model could only achieve two of those three criteria. Arguably, the different approaches to modelling listed in table 20.1 and described above each focus on a different one of Levin's objectives (figure 20.3). While recognising that the boundaries are blurred, it might be said that analytical models focus on generality and precision, empirical models on precision and reality, and (mechanistic) simulation models on generality and realism (Guisan and Zimmermann, 2000).

The case studies also highlight the different approaches taken to model analysis and evaluation. The analytical models described by Bockstael (1996) and Irwin and

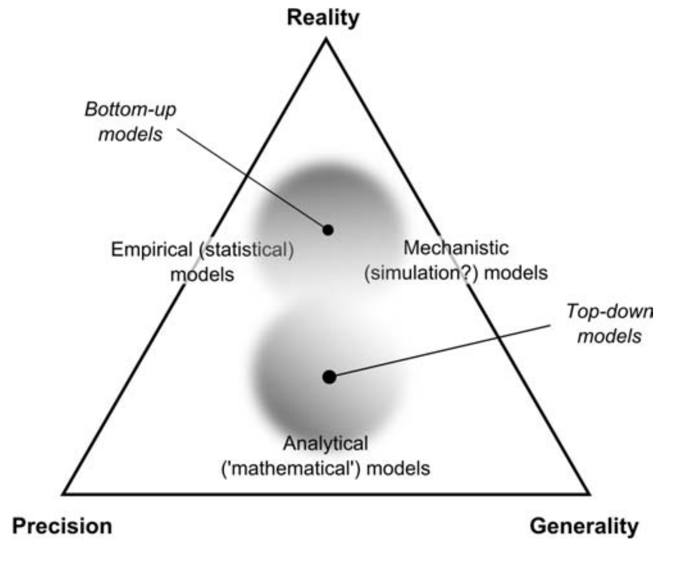

Figure 20.3 A classification of methodological approaches to modelling in relation to the 'goal' of the modelling activity (after Guisan and Zimmerman, 2000); reproduced with kind permission of Elsevier Press.

Geoghegan (2001) and the empirical-statistical models of Millington et al. (2007) rely, largely, on confrontational approaches in that they compare 'real' world observations with model predictions. The tools used in this confrontation vary but include visual comparison of predicted and observed spatial patterns, comparative statistical measures (r^2 and likelihood methods) and pixel-by-pixel comparisons (e.g., the kappa statistic, κ). Jenerette and Wu's 2001 model of urbanisation in Phoenix was evaluated by comparison of the model's predictions with various measures of spatial pattern in the landscape. As their model was stochastic they used Monte Carlo methods (i.e., where did 'real' world observations fall in relation to model estimates?) and avoided pixel-by-pixel confrontation. The agent-based 'Artifical Anasazi' models are evaluated through both confrontation and experiment. The population dynamics produced by the models are visually compared to population changes inferred from archæological reconstructions, and are experimentally evaluated by the researchers 'tinkering' (*sensu* Dowling, 1999) with the model until some adequate resemblance is reached (similar to pattern-oriented modelling).

The case studies also highlight the difficulties in establishing an adequate typology of models and modelling, whether based on methodology or purpose. Methodologically, *all* of the models considered above blur the boundaries between analytical, empirical-statistical and simulation modelling. For example, based on the outcomes of the (empirical-statistical) models developed by Bockstael (1996) and Millington et al. (2007), maps of possible future change may be produced using stochastic simulation. A typology based on purpose is no clearer: all of the examples presented above contain elements of consolidative, integrative and exploratory modelling, and all in some way attempt to improve understanding and to make predictions.

Evaluating the Role of Models in Environmental Geography

A discussion of models and modelling in geography would be incomplete without some mention of the debates about their place in the discipline[4]. During geography's (so-called) 'quantitative revolution', quantitative modelling was embraced as a methodology, peaking in the aftermath of Chorley and Haggett's seminal *Models in Geography* (1967). While models and modelling remain key components in much geographic research (especially in physical geography), geographers continue to debate the appropriate place and use of modelling. Critics of modelling range in position from those who view it as being a worthwhile, but typically poorly done, enterprise, through to those who see it as having little or no place in geography (Flowerdew, 1989). In the following discussion, I will focus on the criticisms put forward by human geographers. This is not because physical geographers all agree about the use and role of modelling, but rather because their debate(s) tend to be rather narrower and methodological (e.g., concerning the appropriateness, or otherwise, of specific techniques and representational assumptions).

In essence, the debate over modelling in geography is an extension of the long-running debate over the usefulness or otherwise of positivism and the scientific method in the discipline (Rhoads, 1999; Demeritt and Wainwright, 2005). Haines-Young (1989) identifies three common critiques of science and positivism in, but not limited to, geography. First, some human geographers complain that modelling, based on abstract quantitative theorising, cannot address the fundamental questions of human geography relating to uniqueness of place, individuality, imagination, morals and æsthetics. Second, there is the realist perspective that truly understanding some entity requires deeper understanding of its structure and the properties that change it and enable it to change. Realists such as Sayer (1992) have argued that the language of mathematics is unable to do this (recall the discussion above of empirical-statistical models as acausal and astructural). Finally, there is the post-modern 'attack' that science and modelling do not hold privileged positions as guarantors of objectivity or truth compared with other approaches, and quantitative modelling is just one of many means of geographic description (Cosgrove, 1989). Science, and indeed knowledge, it is argued, are socially constructed and, as such, are products of the social milieu in which they are created and embedded.

Another, and related, criticism levelled at geographic modelling is that it fails to address the important questions of geography. For example, Harvey (1989) argues that geography is a historical discipline and that the language of mathematics and the positivist approach are ill-suited to the development of theory in this domain (see the realist perspective above). He argues that modelling is limited to repetitive events (cf. Oreskes, 2003, view that prediction is only possible for repetitive systems). Harvey questions what modelling can teach and has taught us about the important historical-geographical shifts that he believes should be the focus of human geography; he states (p. 212) 'those who have stuck with modelling . . . have largely been able to do, I suspect, by restricting the nature of the questions they ask' and bemoans (p. 213) the 'sad degeneration and routinisation of modelling into mere data crunching, numerical analysis and statistical inference *instead of careful theory building*' (my italics). Here lies the crux of the debate: to what extent can models and modelling contribute to effective theory building in geography?

Conclusions

Modelling occupies a central place in geography and related disciplines, and it continues to receive considerable attention in the geographic literature. Although important questions remain about the ontology and epistemology of models and modelling, models are increasingly used in environmental geography to make predictions, to improve understanding, to synthesise and integrate data and to aid in communication. Recent developments in modelling are inextricably intertwined with developments in technology. As new analytical approaches have been developed, new sources of data become available, and computer power has increased and become more readily available, it has become possible to implement ever more detailed ('realistic'?) models. However, detailed and more realistic 'mimics' are not a panacea for the long-standing challenges of identifying appropriate representation and scale. Detailed representation is beguiling, but 'models of this sort may provide an unjustified sense of verisimilitude' (Levin et al., 1997, p. 335). While the pragmatic realist might see ever more detailed models as ever-truer representations, the fact remains that the 'truer' a model, the harder it is to establish its 'truth' (Oreskes, 2003). Likewise, while detailed models may be more empirically adequate, they may be premature and mask a lack of understanding of the entity being modelled (Frigg and Hartmann, 2006). Alongside the development of effective tools for model evaluation, finding the appropriate level of representational detail remains the key challenge for modellers and modelling.

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NOTES

1. Of course, 'complex' also has an everyday meaning, which implies that an entity is not simple and comprises many parts; in essence it is 'complicated'. This everyday use of complexity is commonly used in the modelling literature. For example, detailed models are often described as being 'complex'.
2. *In silico* refers to entities or analyses that solely exist or are performed entirely within a computer.
3. By 'land-cover' I mean the nature of the land surface (e.g. forest, urban, etc.); this does not necessarily imply how the land is 'used', which is encompassed by the more anthropocentric term, 'land use'.
4. In this section, I will draw on contributions to Macmillan's *Rebuilding Geography* as they provide a relatively accessible introduction to what is, at times, a somewhat dense and daunting body of literature.

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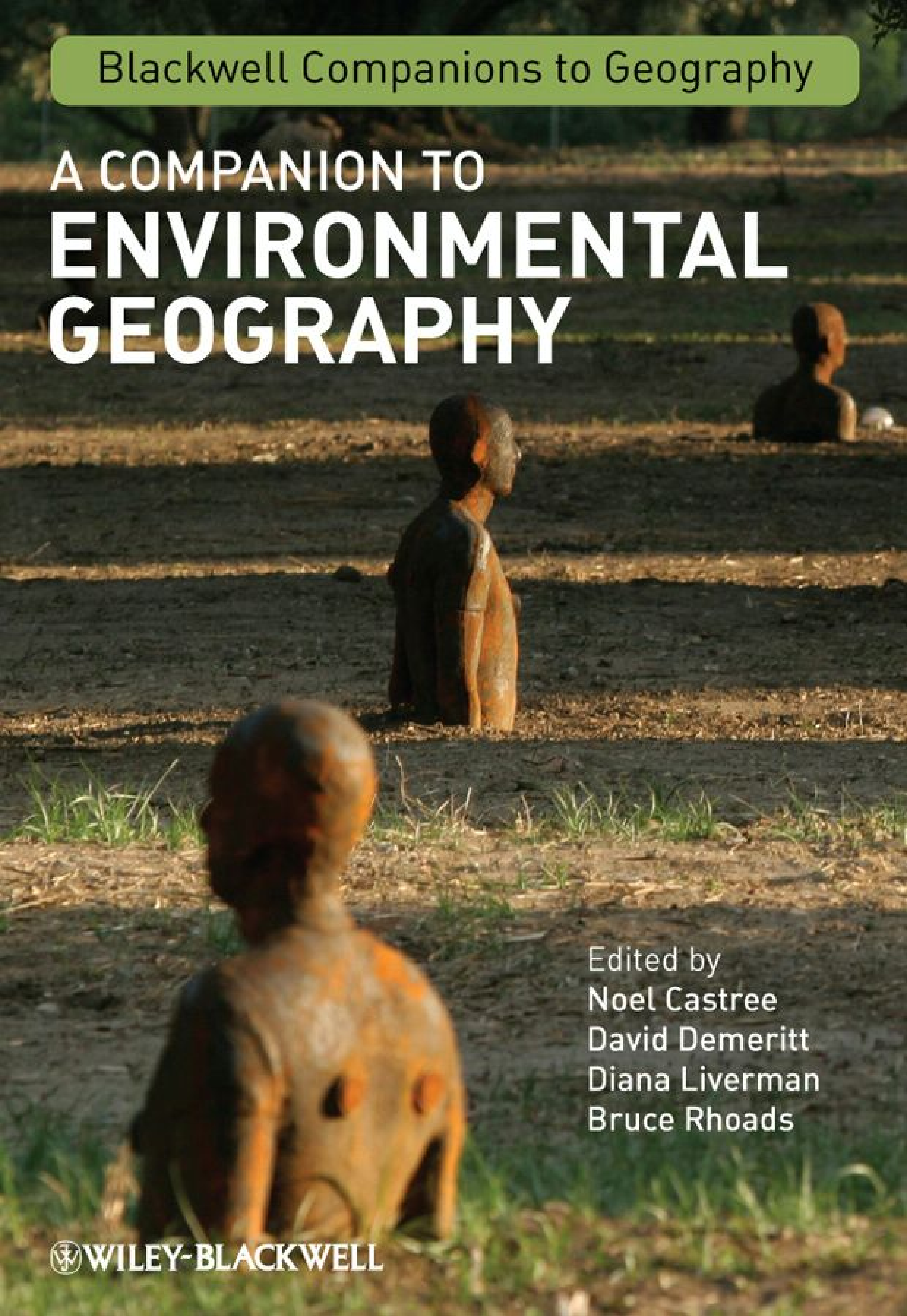

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