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Analyzing Human–Landscape Interactions: Tools That Integrate

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Abstract Humans have transformed much of Earth's land surface, giving rise to loss of biodiversity, climate change, and a host of other environmental issues that are affecting human and biophysical systems in unexpected ways. To confront these problems, environmental managers must consider human and landscape systems in integrated ways. This means making use of data obtained from a broad range of methods (e.g., sensors, surveys), while taking into account new findings from the social and biophysical science literatures. New integrative methods (including data fusion, simulation modeling, and participatory approaches) have emerged in recent years to address these challenges, and to allow analysts to provide information that links qualitative and quantitative elements for policymakers. This paper brings attention to these emergent tools while providing an overview of the tools currently in use for analysis of human–landscape interactions. Analysts are now faced with a staggering array of approaches in the human–landscape literature—in an attempt to bring increased clarity to the field, we identify the relative strengths of each tool, and provide guidance to analysts on the areas to which each tool is best applied. We discuss four broad categories of tools: statistical methods (including survival analysis, multi-level modeling, and Bayesian approaches), GIS and spatial analysis methods, simulation approaches (including cellular automata, agent-based modeling, and participatory modeling), and mixed-method techniques (such as alternative futures modeling and integrated assessment). For each tool, we offer an example from the literature of its application in human–landscape research. Among these tools, participatory approaches are gaining prominence for analysts to make the broadest possible array of information available to researchers, environmental managers, and policymakers. Further development of new approaches of data fusion and integration across sites or disciplines pose an important challenge for future work in integrating human and landscape components.

Keywords Coupled human–natural system · Spatial analysis · Modeling · Human–environment dynamics · Simulation

Introduction

Humans have transformed as much as half of the land's surface (Vitousek and others 1997), biodiversity loss continues at an alarming rate (Butchart and others 2010), and climate change is negatively impacting human and biophysical systems (IPCC 2007). Research has increasingly shown that human and environmental systems can behave in unpredictable ways (Folke 2006; Liu and others 2007a; Liu and others 2001; Werner and McNamara 2007). Making management recommendations in light of these findings require methods that can integrate a broad array of data types from multiple sources. For example, it is not unusual for a single study of human–landscape processes to incorporate remote-sensing data from multiple sensors, time series of ecological data collected from plots or

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transects, topographic data, hydrological data, information on species distribution or habitat usage, and social information from surveys and interviews. For each of these types of data an extensive literature exists in relation to analyzing that particular type of data in isolation. A challenging task for the researcher investigating human–landscape interactions is to reveal a coherent picture that takes into account *all* of these sources of information. Environmental managers also need this kind of integrated analysis.

This review is motivated by this need for ways to integrate and present information in analysis of human–landscape systems. One difficulty faced by researchers is that human–landscape interactions occur across a range of temporal and spatial scales (characterizing the length of time or spatial extent over which a process acts). Sociologists and social geographers have written on the influence of social practices, technological development, and economic structures on conceptions of space and time (Hägerstrand 1966; Harvey 1990; Thrift 2001), and physical geographers have noted the range of spatial and temporal scales across which landscape processes occur (Kirchner and others 2001; Werner and McNamara 2007; Wolman and Miller 1960). We will briefly discuss several examples here; see Harden (this volume) for a more detailed review of the literature on human–landscape interactions. Taking human–climate interactions as an example, weather variation on an hourly daily timescale can lead to flooding and to drastic alteration of the landscape ($\sim$100 km spatial scale), leaving a lasting imprint on society (NCVST 2009). Climate variation on longer interannual and decadal to centennial timescales can impact sensitive ecosystems (IPCC 2007) and agriculture (Howden and others 2007), and potentially affect population processes such as migration (Brown 2008) over a larger spatial scale ($\sim$1,000 km). Similarly, human actions such as land-use and land-cover change, and emission of greenhouse gases can, in turn, feedback on climate (regional-global spatial scale, IPCC 2007; Olson and others 2008). Human–landscape systems can, therefore, be characterized at a range of levels within a spatial and temporal hierarchy (Malanson 1999; Manson 2001; Werner and McNamara 2007).

Research has also shown that human–landscape systems can behave in unpredictable, nonlinear ways (Folke 2006; Liu and others 2007a; Werner and McNamara 2007). Environmental managers must, therefore, consider the possibility of emergent "surprises"—or unexpected results following management interventions—due to complex interactions within or among human–landscape systems (Liu and others 2007a). For example, policies in a protected area might lead to an increase in habitat loss by changing incentive structures such that local families desire a smaller family size (Liu and others 2001).

Understanding these systems is a daunting challenge for analysts. Researchers in the field come from a broad range of disciplines (ecology, biology, the earth sciences, sociology, geography, economics, etc.). Many successful analyses use interdisciplinary approaches and a range of methods to address research questions from a variety of angles. Complexity theory is one common theoretical approach used to understand human–landscape systems (Arthur 1999; Axelrod and Cohen 2000; Crawford and others 2005; Manson 2001). Complex systems are often composed of a hierarchy of constituent elements (as in our human–climate example above, Manson 2001; Werner and McNamara 2007). The relationships between these components (together with feedbacks and interactions occurring across spatial and temporal scales) in part determine the dynamics of complex systems. As stated by Manson, "A complex system is defined more by relationships than by its constituent parts" (Manson 2001). In a human–landscape system with relationships between many different constituent parts at different levels in a scalar hierarchy (individuals, households, neighborhoods, regions, states, planners, developers, etc.), the effects of interactions between agents are essential. These interactions can lead to widely divergent outcomes depending on the "initial conditions" in a system (the initial characteristics of each constituent agent and the initial layout of the environment, Brown and others 2005; Lorenz 1963; Manson 2001). The focus in complexity theory on interactions between individual constituents of a system is similar to the actor-network theory (ANT) framework in sociology. ANT "extends the word actor—or actant—to *non-human, non-individual* entities" (Latour 1996, original emphasis). ANT considers the relationships and interconnections between entities as essential in defining agency (or "the ability to act" Aitken and Valentine 2006), with agency not restricted to the human components of a system (Bosco 2006).

Drawing on these theoretical approaches, the vulnerability analysis framework (Turner and others 2003) and the coupled human and natural systems (CHANS) framework (Liu and others 2007b) are two approaches that have come to the fore in human–landscape analysis. Both advocate use of an array of information and tools of analysis to connect components or subsystems of human–landscape system across scales. Analysts, therefore, need to have some familiarity with the standard methods in other fields, in addition to those of their own discipline. human–landscape researchers have developed their own analysis tools (such as simulation methods), but they still must connect with the other literatures, particularly to coherently communicate findings with policymakers. The objective of this review is to provide an overview of the tools currently used in human–landscape analysis, to give insight on the strengths and weaknesses of each tool, and to provide guidance to

Table 1 Overview of integrative methods in human–landscape research

Method	Examples
Statistical methods	Descriptive statistics, regression analysis, multi-level modeling, survival analysis, Bayesian data fusion
GIS and spatial analysis methods	GIS analysis (overlay, buffering, spatial joins, etc.), geographically weighted regression (GWR), spatial regression models, space–time analysis
Simulation approaches	Cellular automata, agent-based modeling, participatory modeling
Mixed methods	Alternative futures modeling, integrated assessment models

analysts on where and how these tools are best applied. Instead of discussing each method in detail, we aim to provide readers with an understanding of the established and developing methods in human–landscape analysis and, for each method, to highlight an example of their application in the literature. We also point toward other sources for further, detailed review of specific methods.

Strategies and tools for analyzing human–landscape systems are inherently difficult to categorize, given the varied array of methods and data types analysts encounter. To structure our review we focus on four key areas (see Table 1): statistical methods (Sect. Statistical Methods), GIS and spatial analysis methods (Sect. GIS and Spatial Analysis Methods), simulation approaches (Sect. Simulation Approaches), and mixed methods techniques (Sect. Mixed Methods Techniques). We conclude with a discussion of the remaining key challenges for integration in human–landscape research (Sect. Conclusions).

Statistical Methods

Commonly used regression techniques (Sect. Regression Techniques) remain important for human–landscape research, but several less commonly applied techniques are beginning to show influence in the field. Survival analysis (Sect. Survival analysis) shows great promise as the number of longitudinal human–landscape datasets has begun to increase. Data fusion methods (Sect. Bayesian Methods) are only just beginning to appear in the human–landscape literature, but these approaches promise to have greater impact as they mature.

Regression Techniques

Regression techniques (ordinary least squares (OLS), generalized linear models (GLMs), etc.) remain heavily used for studying human–landscape systems, particularly in the geographic (Serra and others 2008; Wandersee and others 2012; Weeks and others 2010) and sociology and demography (Axinn and Ghimire 2011; Lee and others 2008) literatures. Although regression approaches (when compared to simulation methods, for example) are limited in their ability to consider dynamics, and are less capable of handling complexity (such as cross-scalar interactions), and reciprocal causation, their relative ease of implementation, interpretation, and presentation make them attractive to many analysts. Not every study needs to make use of more complex techniques like Bayesian data fusion (BDF) (Sect. Bayesian Methods) or simulation modeling (Sect. Simulation Approaches). Analysts seeking to estimate relative effect sizes or to gauge initial empirical support for a proposed human–landscape link (human influence on habitat change for example) can make fruitful use of relatively simple statistical methods. Even when more complex techniques are used, regression approaches remain valuable for model parameterization and validation using empirical data (An 2012).

Multiple regression techniques are particularly useful for establishing potential human–landscape relationships, allowing analysts to compare the relative effects of a few covariates of interest, while controlling within the model for potential confounding factors. Examples of multiple regressions can be found throughout the literature; we will not discuss these basic methods in detail here. Multi-level modeling, however, is a statistical framework that may be less familiar to human–landscape researchers, but that has much to offer for its ability to apportion the variance in the data according to different hierarchical levels (Goldstein 1999).

In a hierarchically structured dataset (with observations at the individual, household, and neighborhood levels, for example), simple statistical techniques such as OLS would be inefficient and could provide biased estimates of regression coefficients due to correlations in the error terms between observations from the same group (e.g., neighborhood or household). If we are seeking to predict land-use decisions from a set of individuals from a hierarchically structured study, we should not expect individuals that share the same neighborhood to provide statistically independent observations. Given their common exposure to similar neighborhood characteristics (access to services, economic opportunities, etc.) we would expect some correlation in the actions or characteristics of a set of individuals from the same neighborhood. Multi-level techniques allow for accounting for this covariance structure in the model (Gelman and Hill 2007; Goldstein 1999; Jones 1991; Subramanian 2010), and have been applied to many social and environmental datasets (Ghimire and Axinn 2010; López-Carr and others 2012; Pan and

Bilsborrow 2005; Weeks and others 2010; Yabiku 2006). The inclusion of spatial effects within a multi-level model is an active research area (Corrado and Fingleton 2011).

Example Application of Multi-variate Regression

One recent example of multi-variate regression in the human–landscape literature comes from a study in the Fanjingshan National Nature Reserve (FNNR) in China—a reserve established to protect habitat for the endangered Guizhou golden monkey (*Rhinopithecus brelichi*). Wandersee and others (2012) use multi-variate logistic regression to explore the effect sizes, direction (positive or negative), and significance of a number of variables in determining people's perceptions of their environmental impact in the reserve. Using a simulation approach (Fig. 1), they graphically illustrate the uncertainty in their estimate of the effect size of the key predictor in their model (observation of the golden monkey) on local individuals' perception that they personally affect the environment. Wandersee and others (2012) demonstrate the utility of statistical approaches for testing hypothesized human–landscape links in an easily communicated framework.

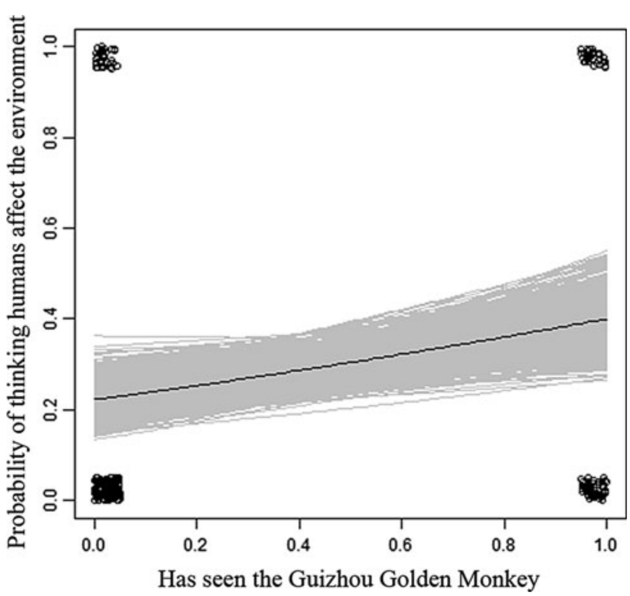

Fig. 1 Simulated uncertainty in regression coefficient (dark line and shaded simulations from 1000 repetitions), from logistic regression predicting perception of personal environmental impact based on contact with the endangered Guizhou golden monkey. The corners of the plot show the joint distribution of the two variables. Figure reprinted from Ecological Modelling, 229, Wandersee, S. M., L. An, D. López-Carr, and Y. Yang., Perception and decisions in modeling coupled human and natural systems: A case study from Fanjingshan National Nature Reserve, China, pages 37-49, Copyright 2012, with permission from Elsevier

Survival Analysis

Survival analysis is particularly useful for investigating time series data such as those that might arise from multi-temporal remote-sensing images or longitudinal social surveys. Survival analysis has traditionally been used in engineering for time-to-failure studies (McPherson 2010; Xie and Lai 1996), in medical sciences for investigating survivorship following a treatment (Hosmer and others 2008; Klein and Moeschberger 2010; Selvin 2008), in the demographic literature for hazard analysis (Barber and others 2000; Reardon and others 2002), and in the operations research literature for applications such as credit scoring or customer loyalty (Larivière and Van den Poel 2004; Oakes 1983; Stepanova and Thomas 2002). An and Brown (2008) present a seminal framework in regard to its potential strengths in land change science. Survival analysis is applicable when the time until occurrence of an event, measured with varying degree of precision, is the dependent variable of interest (Harrell 2001), and such events are associated with variables that have changing values over time (Allison 1995; An and Brown 2008).

Two key concepts of survival analysis are the survival function (a general indicator of what proportion of units, which might be individuals or land parcels, remain unchanged over time) and the hazard function (hazards can be understood as the risk of change that each unit of analysis is subject to over time) (An and Brown 2008). Survival analysis can also neatly handle data censoring (Harrell 2001), including situations in which the event of interest is known to have happened before a specific time (left censored), happened between two time points (interval censored), or NOT happened until a specific time (many times the end of the corresponding study time frame; right censored). Censoring commonly arises with both human and environmental data—whenever we have observations at discrete-time points rather than continuously, data censoring occurs.

Using survival analysis, questions that can be addressed include the impact of landscape change on human behaviors such as migration (Henry and others 2004; Massey and others 2010), marriage timing (Yabiku 2006), or fertility (Ghimire and Axinn 2010; Ghimire and Hoelter 2007). Researchers can also use survival analysis to investigate landscape transitions as a result of anthropogenic activities, treating individual land parcels as the unit of analysis (An and others 2011; An and Brown 2008). An and Brown (2008) used survival analysis in conjunction with GIS modeling and remote-sensing data to explore land-use change in southeastern Michigan, finding that survival analysis is uniquely well-equipped to handle temporal complexities, compared to traditional statistical techniques.

Usage of survival analysis can present some complications. Changes in the unit of analysis over time (e.g., changes in the size or shape of a parcel in land change studies) can be a challenge. Also, correlations between events at different time periods (e.g., accounting for reduced supply of land in later time periods due to prior development) are difficult to handle, though this problem is no worse with survival analysis than with other statistical methods (An and Brown 2008). For more on applying survival analysis to human–landscape analysis, see Vance and Geoghegan (2002), Irwin and Bockstael (2002), An and Brown (2008), and An and others (2011). Generic literature about the technique can be found in Allison (1995), Harrell (2001), Hosmer and others (2008), or Klein and Moeschberger (2010).

Example Application of Survival Analysis

The usefulness of the survival analysis framework in human–landscape analysis is demonstrated by a study of exurban land development in Southeast Michigan (An and others 2011). An and others (2011) examine the role of geographic, biophysical, and socioeconomic factors in determining the hazard of farm parcel development into residential land, using a parcel level dataset constructed from aerial photos taken approximately every 10 years from the 1960s–2000s. The paper leverages the ability of survival analysis to handle a parcel level dataset with data censoring, while also considering competing risks (farm parcels can be developed into different types of residential parcels). As seen in (Fig. 2), an advantage of survival analysis compared to ordinary regression techniques is that with survival analysis changes in hazards can be estimated over time. An and others (2011) found that the hazard of conversion of farm parcels to residential parcels varied over time, and varied depending on the type of subdivision.

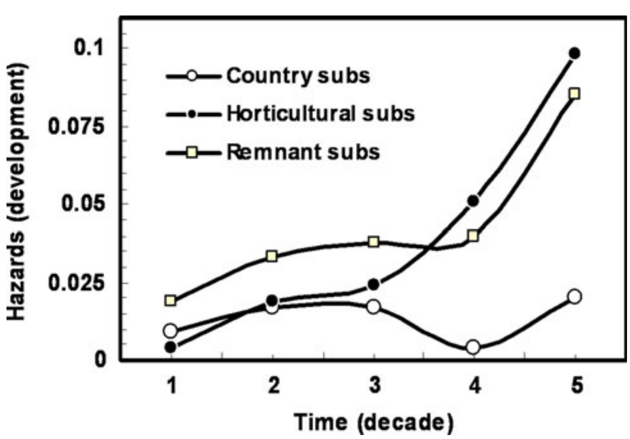

Fig. 2 Hazard rates (calculated over a span of 50 years) for development of farm parcels in southeastern Michigan into three different types of subdivisions. Hazard can be understood as the instantaneous risk of development of a parcel (An and others 2011; An and Brown 2008). Figure reprinted from Journal of Land Use Science, 6 (1), An, L., D. G. Brown, J. I. Nassauer, and B. Low., Variations in development of exurban residential landscapes: Timing, location, and driving forces, pages 13-32, Copyright 2011, with permission of the publisher (Taylor & Francis Ltd, http://www.tandf.co.uk/journals)

Bayesian Methods

Bayesian methods are increasingly prevalent in investigations of human–landscape systems. Bayesian methods differ from the perhaps more familiar "frequentist" approaches to statistical analysis on which classical approaches to hypothesis testing are based. One key difference between the two is that in frequentist approaches to statistical inference, model parameters are treated as fixed unknown quantities, whereas in a Bayesian approach, model parameters are treated as unknown random variables (Gelman and others 2003; Hobbs and Hilborn 2006). Using a Bayesian approach, complicated model structures can be represented, and the probabilities of competing hypotheses can be compared (Hobbs and Hilborn 2006).

In both frequentist and Bayesian approaches, data (Y) are treated as having come from a sampling distribution $f(Y|\theta)$ (read "a function of data Y given parameter θ") (Link and others 2002). The analyst can estimate the model parameter(s) (θ) based on the observed data (Y). In a frequentist approach, θ is treated as an unknown fixed quantity, whereas in Bayesian analysis, θ is treated as a random variable with a corresponding distribution $f(\theta|Y)$ (referred to as the "posterior distribution") (Link and others 2002). Using Bayes theorem, we can calculate the posterior probability associated with the model parameters conditional on the observed data, taking into account prior knowledge we may have about the problem. For an introduction to Bayesian techniques aimed at those already familiar with frequentist statistics, see Hobbs and Hilborn (2006); Gelman and others (2003) provide a more extensive background on Bayesian statistics. Link and others (2002) and Clark (2005) review applications of hierarchical models, and Calder and others (2003) discuss the application of Bayesian state-space methods in population modeling.

A strength of Bayesian analysis is its ability to consider directly the probability of alternative hypotheses (Gelman and others 2003; Hobbs and Hilborn 2006). We can also use a Bayesian framework for data fusion—the problem of how to combine "different sources of information into a single final result" (Fasbender and others 2008). BDF is a developing field for integrating different types of data of varying spatial and temporal resolutions. A simple example will help to conceptualize the concept of data fusion: suppose we are trying to merge a set of measurements where multiple measurements, using different instruments, have been taken at the same location (for example, panchromatic and multi-spectral sensors). Each sensor provides slightly different information on land cover, our phenomena of interest. A BDF framework can handle this case by including it in the definition of the posterior and the prior conditional probability distributions. In this case we would have the posterior distribution $f(z|y_s, y_p)$ where y_s refers to the multi-spectral observations for a pixel, y_p the panchromatic, and z is our outcome variable (Bogaert and Fasbender 2007; Fasbender and others 2008).

Although much work in data fusion has focused on military applications, data fusion techniques are seen with increasing frequency in the remote-sensing literature (see Zhang 2010, for a recent review). BDF offers a probabilistic framework within which multiple data sources, possibly at different spectral, spatial, and/or temporal resolutions, can be neatly handled (Bogaert and Fasbender 2007; Fasbender and others 2008; Mohammad-Djafari 2003). Solberg and others (1994) presented an early approach to fusing Landsat TM and synthetic aperture radar (ERS-1) imagery using a Bayesian framework. Other recent work includes Bogaert and Fasbender (2007) on spatial prediction, Urban and Keller (2010) and Olson and others (2012) on climate data, and Peng and others (2011) for a review of data fusion approaches in ecology. Use of BDF in human–landscape research is still rare—future research is needed on the most appropriate applications of BDF in human–landscape studies, and on how BDF might be integrated with other methods (e.g., with qualitative data or to support development of simulation models).

Several software tools are capable of fitting Bayesian models. WinBUGS (Lunn and others 2000) is readily available online, as is its open-source and multi-platform successor OpenBUGS (Lunn and others 2009). Both use Markov Chain Monte Carlo (MCMC) methods. OpenBUGS functionality can also be accessed from within the R statistical computing environment using the “BRUGS” package (Thomas and others 2006). Although BDF is new to the human–landscape literature, the promise of BDF is great—we can expect to see growing usage of BDF and other data fusion approaches in the future.

Example Application of BDF

There are few examples of BDF usage in the human–landscape literature, but a remote-sensing study by Fasbender and others (2008) shows the potential of BDF approaches for fusing multiple data sources together, of varying spatial resolutions. Fasbender and others (2008) compare BDF with other approaches for pan-sharpening IKONOS imagery, finding that the BDF method consistently performs well compared to other methods. An additional advantage they note is that the BDF framework offers the analyst an opportunity to tune the fusion—weighting alternative sources of information more heavily than others if desired (Fasbender and others 2008).

GIS and Spatial Analysis Methods

Geographic Information Systems (GIS) can efficiently handle spatial data of different types (raster, vector) and from different spatial scales, and are widely used for planning and analysis of human–landscape systems. Spatial analysis can be useful in handling spatially explicit (often spatially auto-correlated) data within a regression framework (and sometimes within a GIS). First, we will discuss GIS tools (Sect. GIS Tools). We will follow with an introduction to the more analytic approaches for spatial data (Sect. Spatial Analysis and Modelling).

GIS Tools

Geographic Information System (GIS) tools can be very useful for data integration and manipulation. A GIS allows the user to take advantage of spatial analysis tools like overlaying, buffering, spatial joins, etc. to compare spatial datasets. The major GIS tools (ArcGIS, IDRISI, Quantum GIS, GRASS, etc.) all have these basic capabilities. More advanced spatial analysis features are beginning to appear in GIS packages—geographically weighted regression (GWR) is available in the latest version of ArcGIS, and Quantum GIS can be connected with the R statistical computing environment.

An edited volume by Fox and others (2002) provides a number of case studies of how to link social and environmental datasets using GIS. A recent review by French (2010) shows how GIS tools are being used in archeological studies to understand past human–landscape dynamics, by integrating point-observations and micro-level archeological studies into a broader scale, landscape view. Other studies are utilizing GIS tools as a key part of multi-criteria decision analysis (MCDA) frameworks (Berger 2006; Girard and Toro 2007; Phua and Minowa 2005), to allow inter-comparison of alternative scenarios and policies from within an integrated spatial framework.

GIS tools can also be used for spatial analysis and modeling (more in Sect. Spatial Analysis and Modelling)—Mörtberg and others (2007) use GIS (ArcGIS and IDRISI) to model habitat for a set of focal species under three alternative development scenarios for the Stockholm, Sweden region. Simple rule-based models can also be implemented in GIS, using map algebra to combine layers and datasets. Flood modeling is one example: Brown (2006) use a GIS to implement a series of transition rules to

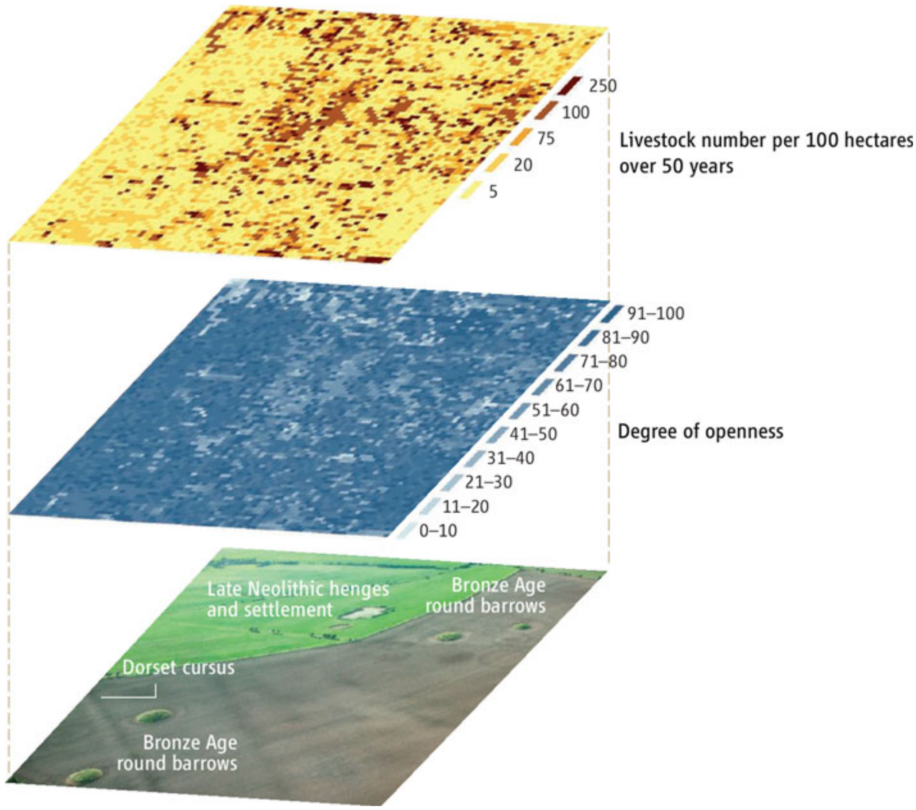

Fig. 3 Example of a GIS model merging archaeological and environmental data to simulate historical human–landscape interactions in Cranborne Chase in central southern England. The bottom depicts known prehistoric sites, the middle the degree of canopy openness predicted from pollen data, and the top the predicted livestock density required to maintain the observed degree of canopy openness. Figure reprinted from French (2010). Figure in French (2010) was adapted by D. Redhouse from Samarasundera, E. 2007. "Towards a dynamic ecosystem model for the Neolithic upper Allen valley". In: Prehistoric landscape development and human impact in the upper Allen valley, Cranborne Chase, Dorset, McDonald Institute Monographs., eds. C. French, H. Lewis, M. J. Allen, M. Green, R. Scaife, and J. Gardiner, 197–207. McDonald Institute for Archaeological Research. Reprinted with permission of C. French and D. Redhouse

model sea-level rise impacts in North Norfolk, UK, under a number of different policy scenarios.

The strength of GIS tools is their ability to integrate a wide array of data sources within a unified framework. However, GIS software has advanced to the point where spatial prediction problems and simple spatial models can appear trivial. It is always important to remember the limitations inherent in any type of modeling, and to take into consideration the underlying data and statistical and theoretical support for map products produced with off-the-shelf GIS packages. When presenting model results, communication of uncertainty, understanding of the model, and recognition of the assumptions that went into it, all remain essential parts of the analytical process.

Example Application of GIS Modeling

As reviewed by French (2010), archeological studies have incorporated GIS modeling quite successfully to study human–landscape relationships on century-millennial timescales. One example is Samarasundera (2007), who used a GIS to combine spatial data sources from archeological surveys, pollen surveys, and other data sources to develop a model of prehistoric grazing intensity in Cranborne Chase in central southern England (Fig. 3). This model allowed Samarasundera to determine that grazing alone (as opposed to agricultural intensification) could have led to the observed forest recession in the area (French 2010; Samarasundera 2007) .

Spatial Analysis and Modeling

Spatial analysis and modeling is a broad umbrella, under which a range of operations, analyses, and methods are embedded. The predominant characteristic of spatial analysis and modeling is to deal with data in which geographic locations are intrinsically important. Thus, spatial analysis and modeling have close connection with GIS tools (Sect. GIS Tools). We separate them here to emphasize their arguably more analytical (rather than mapping and visualization) nature. A plethora of methods and techniques have been made available in the last couple of decades for spatial analysis and modeling; for a general overview see the book edited by Maguire and others (2005).

Worthy of mention is the rich set of tools from spatial econometrics. Observations from social survey and environmental datasets often cannot be considered statistically independent due to spatial autocorrelation. Samples from the same area might be expected to experience similar environmental conditions, leading to spatial autocorrelation in the residuals of simple OLS models if the spatial structure of the data and process are not taken into account. Failure to account for spatial autocorrelation can lead to bias and even misleading estimates of regression coefficients (Getis 2009). For background on current techniques in spatial analysis, see Haining (2003), Fischer and Getis (2009), and Fotheringham and Rogerson (2009). To account for spatial autocorrelation, one option is to use simultaneous autoregressive (SAR) models (Getis 2009). For spatially varying relationships, GWR may be used to examine how relationships vary across space (Fotheringham and others 2002).

Spatial autocorrelation may exist in the residuals due to the presence of unobserved covariates (indicating a spatial error model might be appropriate), or due to spatial dependence in the dependent variable itself (suggesting a spatial lag model), or due to both simultaneously (Anselin and Lozano-Garcia 2009; Getis 2009). Lagrange multiplier (LM) tests are one method of testing for spatial effects in regression residuals (Anselin and Rey 1991). Inspection of semivariograms is another technique for investigating spatial dependence. The GeoDa software package (http://geodacenter.asu.edu) is a fully featured, stand-alone package for geospatial analysis (Anselin and others 2006). Spatial analysis can also be conducted from within the R statistical computing environment using the "spdep" package (Bivand 2012; Bivand and others 2008).

An increasing trend under the umbrella of spatial analysis and modeling is the "space–time analysis," a rapidly growing research frontier in geography, particularly in GIScience. Its increasing popularity was evidenced by the special symposium "Space–Time Integration in Geography and GIScience" in the 2011 conference of the Association of American Geographers and the "Space–Time Modeling and Analysis Workshop" (of the Environmental Systems Research Institute) which attracted a large number of scientists and engineers. Space–time analysis emphasizes not only spatial heterogeneity but also temporal variability in the processes or phenomena of interest. Scientists have been developing theories, metrics, and tools to visualize and understand how economic activities or inequalities (Rey and others 2011; Ye and Carroll 2011), crime rates (Wu and others, in press), individual behavioral patterns (Kwan and Lee 2004; Sang and others 2010; Shaw and others 2008), etc. may spread and change over both space and time. Worthy of mention is the theoretical development in time geography (Shaw and others 2008; Yuan 2007). Two useful tools in this area are the ArcGIS extension tool "Extended Time-Geographic Framework Tools" (http://web.utk.edu/~sshaw/NSF-Project-Website/default.htm; (Shaw and others 2008) and the open source "Space–Time Analysis of Regional Systems" (http://ideas.repec.org/p/wpa/wuwpur/0406001.html; Rey and Janikas 2006).

Example Application of Spatial Analysis

An example application of spatial analysis using GWR is in a recent paper by López-Carr and others (2012). López-Carr and others used GWR and multi-level regression to explore the predictors of forest cover change in Guatemala, using survey and agricultural census data to measure demographic change, and MODIS (Moderate Resolution Imaging Spectroradiometer) satellite imagery to measure change in forest cover. GWR was used to explore spatial variation in the coefficient of determination (R^2) and in the regression coefficient estimates. As seen in (Fig. 4, left), local R^2 values from GWR show that the regression model performs the best in the north and southeast of Guatemala, suggesting that in other areas of the country the explanatory variables included in the model do a poor job of explaining observed forest cover. GWR also allows investigating spatial variation (spatial non-stationarity) in the estimated regression coefficients—as seen in (Fig. 4, right); an increase in population density appears to be associated with a decrease in forest cover in northern and central Guatemala, but to have the opposite effect in the southern part of the country. This spatial variation could not be explored with non-spatial regression techniques..

Simulation Approaches

Simulation approaches for modeling human–landscape systems have seen heavy development in the past three decades. Simulation approaches allow integration of a broad array of data sources in a dynamic framework that can consider feedbacks and non-linearities. Cellular automata and agent-based modeling (ABM) are two of the most heavily used simulation approaches in current human–landscape research. We will first outline cell-based spatial models, particularly cellular automata (Sect. Cell-based Spatial Models), and then we will discuss ABM, including recent developments in participatory ABM (Sect. Agent-Based Modeling).

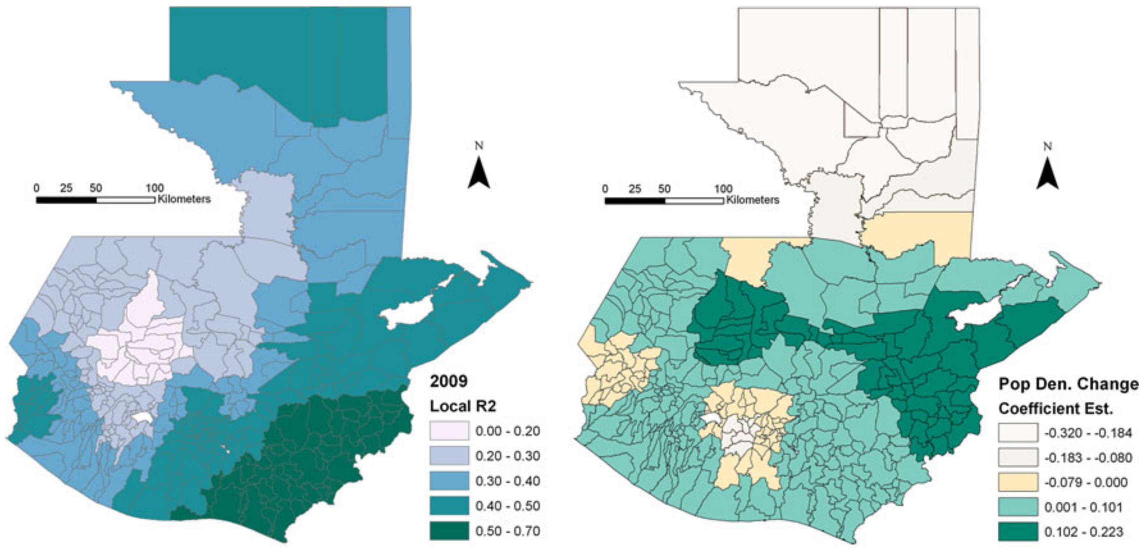

Fig. 4 Results of geographically weighted regression (GWR) predicting percent woody cover in 2009 in Guatemala. Pictured are the local R2 values from the GWR regression (left) and the coefficient estimates for the percent population density change from 1990 to 2000 (right). Adapted figure reprinted from Ecological Modelling, 229, López-Carr, D., J. Davis, M. M. Jankowska, L. Grant, A. C. López-Carr, and M. Clark., Space versus place in complex human–natural systems: Spatial and multi-level models of tropical land use and cover change (LUCC) in Guatemala, pages 64-75, Copyright 2012, with permission from Elsevier

Cell-based Spatial Models

Cell-based spatial models are a type of bottom-up simulation approach often employed to understand human–landscape systems. Cell-based models invoke a set of rules (e.g., functions, logic) to update the states or values of cells (units of the landscape under investigation) through time (Goodchild 2005). Of particular interest within this type of models are cellular automata, which are rooted in the lattice network by Stanisław Ulam, the self-replicating automaton by John von Neumann, and the famous "game of life" cellular automaton by John Conway (Wolfram 2003). In a cellular automaton model, the landscape under investigation consists of grid of cells, and each cell is in one of several discrete states (e.g., urban vs. non-urban; forest, agricultural, grassland, etc.) at each time step. As time goes on, the state of each cell is updated according to certain rules, which consider the state of both the cell under investigation and a set of pre-defined neighboring cells. CA has been extensively used to understand urban growth or expansion (Batty and others 1997; Batty and Xie 2005; Benenson and Torrens 2006; Clarke and others 1997; Clarke and Gaydos 1998; Torrens and Benenson 2005).

Cell-based spatial models have had successes in a wide range of applications; readers with interest are referred to Maguire and others (2005). Due to their limitations in modeling activities of mobile entities (e.g., animals, people) as well as human decisions in human–landscape systems, cell-based spatial models are often complemented by agent-based models (ABMs), our topic in Sect. Agent-Based Modeling.

Example Application of Cellular Automata

While some of the software references are now a bit dated, Batty and others (1997) still provides a good introduction to modeling urban landscapes using cellular automata. Arguing that cellular automata models are well-suited to modeling urban growth, Batty and others describe different set of rules that can generate forms close to those we see in an urban setting, including regular patterns (similar to gridded networks of roads). The paper provides an example of how cellular automata models can be used as an experimental tool to study patterns of development, including neighborhood effects (development of a cell may depend to some extent on development of its neighbors), constraints, "memory" (the decision on whether to develop a cell is dependent in part on past development decisions at that cell) and randomness.

Agent-Based Modeling

Partially rooted in complexity theory, ABM (equivalent to "individual-based modeling" in the ecology literature) represents human–landscape systems as a series of interacting components (agents or objects) at various levels of hierarchical organization (Sect. Introduction). An agent-based model (also ABM) focusing on land-use and land-cover change, for example, might represent several classes of agents, including individual agents (people), household agents (composed of individual agents), neighborhood agents (composed of household agents), and policy agents (a class representing the combined influence of policymakers). The structure of ABM allows researchers to consider the possibility of emergent phenomena that may arise from lower level interactions (Liu and others 2007a; Werner and McNamara 2007). See the recent paper by Manson and others (2012) for a discussion of ABM from a complexity perspective.

ABM is useful to human–landscape analysts due to its ability to integrate data from multiple spatial, temporal, and/or organizational scales, to include heterogeneous agents, their interactions (and resulting emergent phenomena), and to be coupled with cellular models (An and others 2005; Liu and others 2007a; Werner and McNamara 2007). Usage of ABM in the human–landscape field continues to increase rapidly. ABMs have seen much use in land-use and land-cover change research—work aimed at understanding the patterns, processes, and change in human use of land (land-use) and the biophysical attributes of the land surface (land cover, Lambin and others 2001). For a review of ABM in modeling land-use and land-cover change, see Parker and others (2003); for ABM usage in ecology and ecosystem management, see Grimm (1999) or Bousquet and Le Page (2004); for ABM in economics, see Heckbert and others (2010); for ABM in geography and other spatial sciences, see Torrens (2010); for modeling individual-level human decisions in human–landscape systems, see An (2012). Examples of ABM can be found throughout the human–landscape literature (An and others 2005; Axtell and others 2002; Bithell and Brasington 2009; Brown and Robinson 2006; Castella and others 2005; Chen and others 2012; Deadman and others 2004; Entwisle and others 2008; Evans and Kelley 2004; McNamara and Werner 2008; Tews and others 2006).

Although the promise of ABM is great for human–landscape research, as ABMs have grown in popularity, the lack of a common platform and standardized protocols for communication of model structure and results has hampered evaluation of models, complicating comparison across sites, and making duplication of results near impossible (An 2012; Grimm and others 2005; Parker and others 2003). One common framework for ABM description that has seen increasing usage in the literature is the ODD (overview, design concepts and details) framework (Grimm and others 2010; Grimm and others 2005; Grimm and Railsback 2012; Schmolke and others 2010). The Open ABM Consortium (http://www.openabm.org, Janssen and others 2008) maintains a library of ABMs, many of which have adopted ODD. The COMSES (Computational Modeling for SocioEcological Science) network, a National Science Foundation funded project (PI Michael Barton, Arizona State University), is building off the OpenABM framework to promote ABM modeling and education, including hosting an ABM modeling competition (Janssen and Rollins 2011).

Another key challenge for ABM researchers is cross-site comparison and synthesis. ABMs tend to be site-specific, making generalization difficult. Simple models have proven easier to generalize across sites: one example is provided by Acevedo and others (2008), who developed a generic model framework to explore how stakeholder values influence land-use decision- making and land-use and land-cover change. The successful cross-site comparison accomplished by Acevedo and others (2008) exemplifies the advantage of comparative studies of using simplified models. Simple models can more easily be understood and modified as necessary to account for site-specific phenomena while retaining the ability for modelers to compare results across sites.

Several toolkits are available for ABM research. For new ABM modelers, NetLogo (freely downloadable at http://ccl.northwestern.edu/netlogo/; Wilensky 1999) allows users to quickly begin constructing models, with the aid of a graphical interface for model design. Repast Simphony (available at http://repast.sourceforge.net/; North and others 2007) is a Java-based modeling system that supports GUI-based model design, in addition to model development in Logo, Groovy, or Java. See Lytinen and Railsback (2012) for a comparison of the RePast and NetLogo frameworks. Another route modelers pursue is building custom models using their preferred languages or platforms (Matlab, Python, Java, C++, etc.). In this case, care should be taken to insure that model design and structure is clearly communicated, so that those unfamiliar with the chosen language can easily understand results. Standardized model description formats like the ODD framework are particularly important here.

Participatory agent-based modeling (PABM) (similar to the "companion modeling," or ComMod process described in the ecology literature, for example see Ruankaew and others 2010) is an iterative approach to ABM design and modeling that involves stakeholder groups throughout the model development process. This approach directly incorporates local knowledge, insuring the relevance of modeling to stakeholders (Parker and others 2003). In addition, ABM can often provide visual tools in a participatory setting, where stakeholders can review and comment on both model structure and spatially explicit simulation results (Parker and others 2003). When modeling is conducted in concert with stakeholders, an ABM can be used as a "common artificial world" that is a "shared representation" of a coupled human–landscape system (Bousquet and others 2002). Although still a developing research area, participatory modeling approaches have seen used in a range of human–landscape systems, including forestry management (Simon and Etienne 2010), groundwater management (Zellner 2008), land-use and land-cover change (Castella and others 2005; Pak and Brieva 2010), and labor migration in response to fluctuating agricultural productivity (Naivinit and others 2010).

"Mediated modeling" (MM) is a participatory approach that makes use of system dynamics models (which take an aggregate approach to modeling feedbacks and flows in a complex system) and simulation approaches like ABM as part of a larger participatory process that involves stakeholders in model building (van den Belt and others 2010). "Small system dynamics" models take a step back from ABM (which may be developed as a precursor), and include only a small number of feedback loops (8 or less) to present an aggregate picture of system dynamics that may be easier to communicate and understand compared to ABM (Ghaffarzadegan and others 2011). Participatory modeling using role-playing games (RPG) is one of the most direct ways of involving stakeholders in model development. RPGs can assist stakeholders in discussing and understanding an agent-based model, increasing their comfort with the simplifications used in an ABM (Naivinit and others 2010). Experiments combining ABM with RPG exercises have now been carried out in several study regions (see D'Aquino and others 2002 for a brief review).

Example Application of ABM

Agent-based models are well-suited for integrating multidisciplinary research into a unified framework. One example is the authors' work in the Chitwan Valley, Nepal. The Chitwan Valley is a primarily rural agricultural area along the Nepal-India border in south-central Nepal, bordering the Chitwan National Park, a UNESCO World Heritage site that is home to several endangered species. To better understand feedbacks between land-use and land-cover and micro-level human decision-making, we have combined existing results from the peer-reviewed literature with new surveys and analysis to build a spatially explicit agent-based model of the Chitwan Valley (An and others, in preparation; Zvoleff and An, in press). The model contains a population of individuals, households, and neighborhoods taken from survey data, and links them with the landscape using a series of environmental and demographic submodels (Fig. 5). This approach allows researchers to explore different scenarios of human and landscape change. For example, investigators can use the model to explore how changes in household structure, such as the desired family size, might affect fuelwood extraction from local forests (Fig. 6).

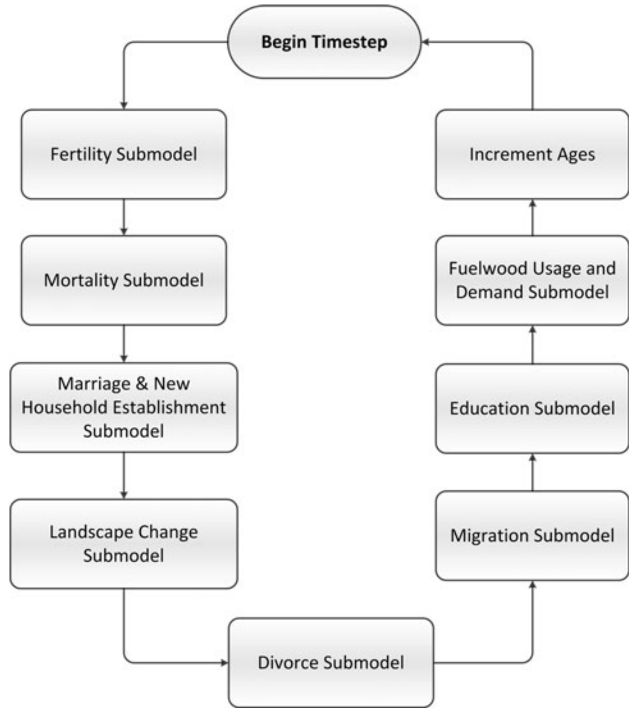

Fig. 5 Processes in the Chitwan agent-based model

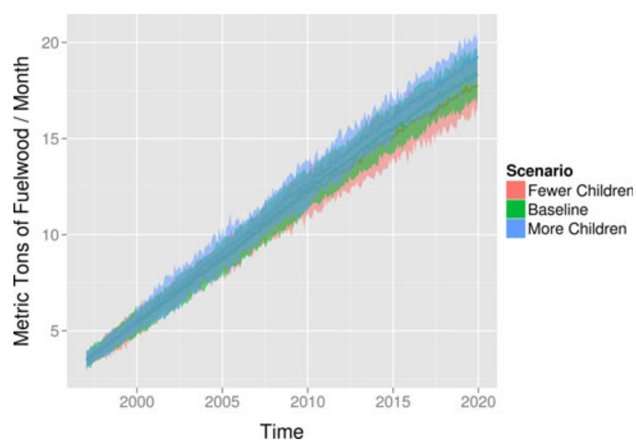

Fig. 6 Example of a scenario from the Chitwan agent-based model, exploring how changes in desired family size might affect total fuelwood consumption in the Chitwan Valley over a 25 year timescale

Mixed-Method Techniques

A significant challenge in human–landscape research is linking qualitative and quantitative data, and communicating modeling results to stakeholders (Lach this volume). Alternative futures modeling (Sect. Alternative Futures Modeling) and integrated assessment models (Sect. Integrated Assessment Models) are two examples of tools that are useful for linking these mixed data types.

Alternative Futures Modeling

Alternative futures modeling (also referred to as scenario analysis) is a strategy that uses a combination of models and (generally) stakeholder involvement to explore a set of scenarios depicting alternative future states of a human–landscape system, usually contingent on present and future actions and particular pathways of policy development. Use of alternative futures modeling for a study does not dictate a particular quantitative modeling strategy (regression analysis or ABM simulation, for example), though the examples in the literature generally use a combination of a spatial simulation models like ABM for modeling human decision-making, with some models including a coupled set of environmental sub-models. The resulting alternative futures (scenarios) can be used as a policy analysis tool—once the potential range of future states of a system has been laid out, policymakers can attempt to develop policies that are likely to be beneficial under the broadest possible range of likely outcomes. The end goal of alternative futures analysis is to develop policies that will be "robust against future surprises" (Hulse and others 2008). Not all alternative futures analyses use ABM or similar simulation models. Some studies' main focus is participatory planning—these studies focus primarily on stakeholder involvement and qualitative comparison of alternative policy scenarios (Daconto and Sherpa 2010). Other studies make use of alternative quantitative approaches, such as linear programing (Bryan and others 2011).

Alterative futures frameworks are advantageous for analysis and integration of human–landscape systems given the high degree of stakeholder involvement in the process, and their relative ease of presentation to and understanding by managers and non-specialists. However, alternative futures approaches may be less likely to consider the possibility of unstable dynamics or "surprises." Hulse and others (2008) found that when two types of scenarios were compared, one with citizen input, the other with an agent-based model and "expert" input from key stakeholders and researchers in the field, the citizen-input model was less likely to consider scenarios with large or abrupt changes from present-day conditions. Careful design of the participatory process may alleviate these concerns to some extent (Ison and others 2010; Johnson and others 2012). However, given the decadal to century-long timescales considered in many alternative futures models, new methods of validation and verification are needed to better communicate the uncertainty in the results, and potential for low-likelihood but high-impact alternative scenarios.

Example Application of Alternative Futures Models

Extensive work has been conducted on alternative futures modeling in the Willamette Basin, Oregon. Bolte and others (2007) present "EvoLand" a model of human–landscape change in the Willamette Basin, that models the decision-making of "actors" (land management decision-makers) as constrained and influenced by cultural and policy "metaprocesses." EvoLand uses a "plug-in" structure to allow the modelers to study how decision-making processes and policy influence various landscape characteristics, such as aquatic and terrestrial habitat and land market values. Guzy and others (2008) use the framework to test the impact of alternative management policies on ecosystem services, while Hulse and others (2008) compare citizen-based and expert-based approaches to scenario building and modeling.

Integrated Assessment Models

Integrated assessment aims to produce information for policy comparison. These models fall somewhere between alternative futures analysis (Sect. Alternative Futures Modeling) and simulation models (Sect. Simulation Approaches), but are generally closer to traditional economic models than other approaches typically encountered in human–landscape research.

Integrated assessment models have thus far had the greatest impact on climate change policymaking (see Salter and others (2010) for a recent review, and Perdinan and Winkler, this volume), though they have also seen some usage in other sectors (see the special issue of *Agricultural Systems* edited by Bezlepkina and others (2011) for a review of current integrated assessment work in agriculture). In climate change studies, integrated assessment models typically couple existing general equilibrium economic models to simplified geophysical climate models (Nordhaus 2011; Nordhaus 2009; Nordhaus and Boyer 1999).

Integrated assessment models of climate change have been criticized as the simplifications necessary for tractable solutions generally eliminate the possibility of different stable equilibrium states, or of unstable dynamics (DeCanio 2003; Werner and McNamara 2007). Another problem encountered with using integrated assessment models for decadal to century-long planning is that to evaluate and compare investments over time, modelers must consider the discount rate. A high discount rate reduces the present valuation of future events (the cost of sea-level rise due to climate change for example). A low discount rate would lead to recommendations to spend heavily now to avoid possible future impacts of climate change (even when the impacts might be low-likelihood, or far in the future). The choice of discount rate can radically affect the results of a study and is not a simple parameter to determine—economically or philosophically (Bell and others 2003; Dasgupta 2008; Portney and Weyant 1999). As with any model, managers need to be aware of the assumptions behind any given integrated assessment model to properly evaluate the model and make management decisions.

Example Application of Integrated Assessment Modeling

The Dynamic Integrated Climate-Economy (DICE) and Regional Integrated Model of Climate and the Economy

(RICE) models are two of the most cited integrated assessment models of climate change (Nordhaus 2011; Nordhaus 2009; Nordhaus and Boyer 1999). The two closely related models consider global climate change using an optimization framework to optimize investments in consumption, capital, and emission reductions over time. The RICE model (the regionally explicit version) breaks the globe into twelve representative regions, each with unique attributes (population growth, technological development, etc.). The model also contains a geophysical module relating economic activity and climate. The coupled model allows exploration of the optimal investment approach (in consumption, capital, and environment) to maximize social welfare over time.

Conclusions

Study of human–landscape systems requires methods that can integrate data or models across spatial and temporal scales, across disciplines, and across levels of organization. Just as no model is perfect, no single tool is sufficient for human–landscape analysis. We have discussed tools from four broad categories: statistical methods, GIS and spatial analysis methods, simulation approaches, and mixed-method techniques. Simulation methods have received the bulk of the focus in the recent literature due to their ability to efficiently handle data from multiple scales and to examine system dynamics, while also integrating well with other methods and approaches, such as participatory research and scenario analysis. However, researchers must keep an open mind, given the diversity of disciplinary approaches in human–landscape research.

The research question in particular should be the primary determinant of what approach to use when examining a human–landscape system (see Table 2). If researchers seek to understand the relative effect of a small number of variables (e.g., household age structure, vegetative cover) with only panel data available, while controlling for potentially confounding factors at a micro-scale (e.g., migration patterns, household economics), statistical methods are likely a good fit. If understanding system dynamics is important, simulation models will likely be most beneficial. If qualitative communication and description of future states of a system over a decadal or century-long timescale is most important, alternative futures approaches or integrated assessment might be most appropriate. Regardless of the chosen approach, the limitations of each strategy must be kept in mind (Table 3). Understanding and communicating uncertainty is a responsibility of all analysts.

A key development in the recent literature is the increasing usage of various participatory approaches to

Table 2 Key questions to consider in choosing an approach for analyzing human–landscape interactions

System feature of interest	Suggested approaches
Dynamics (temporal)	Simulation models (ABM, participatory ABM), survival analysis
Dynamics (spatial)	Cell-based spatial models, ABM, GIS tools
Feedbacks	Simulation models
Outcomes (annual-decadal timescales)	Statistical methods, simulation approaches, mixed methods techniques, Bayesian data fusion
Outcomes (century-millennial timescales)	Integrated assessment, alternative futures
Instabilities or surprises	Simulation approaches
Drivers of change	Regression approaches, spatial analysis and modeling

Table 3 General overview of some of the strengths and limitations of the four categories of methods

Approach	Strengths	Weaknesses
Statistical methods	Good for exploratory analysis	Difficult to examine system dynamics
	Rapidly implemented	Common assumptions (normality and independence of residuals, linearity) often not satisfied in human–landscape studies
	Broadly understood	
	Well-established methods for representing uncertainty	
GIS and spatial analysis methods	Good for exploratory analysis	Some software packages stress visualization over analysis
	Excellent visualization tools	It can be (too) easy to make plots or maps with little theoretical support
	Can easily and precisely (including coordinate transformations, etc.) handle spatial data	Support for temporal dimension traditionally weak in GIS tools
	Can account for spatial autocorrelation	
Simulation approaches	Can integrate data from multiple temporal and spatial scales, can represent hierarchically structured systems, and nonlinear dynamics	Models can be difficult to construct, and are often hard to replicate
	Integrate well with mixed methods approaches	Understanding the structure of complex simulation models can be difficult even for experts
	Good at representing interactions between system components, including feedbacks	Communication of uncertainty sometimes overlooked

Table 3 continued

Approach	Strengths	Weaknesses
Mixed methods	Good at representing qualitative findings	Limitations and assumptions must be clearly communicated (for example discount rates in integrated assessment models)
	Good for decision-making under uncertainty—alternative policies can be explored	Wide range of techniques—readers may be unfamiliar with individual methods
	Can consider long time horizons (decades-centuries) using qualitative storylines	

increase stakeholder involvement. Participatory modeling strategies (cooperative scenario development, role-playing games, etc.) are becoming more common, and may aid analysts in ensuring that their models are responsive to the needs of managers and other stakeholders in human–landscape systems. Participatory modeling strategies may also aid in developing and validating more useful models.

Challenges still remain in human–landscape research. Advancement in dynamic modeling approaches (such as ABM) is important, but an increasing need exists for cross comparison of models, and generalization of findings across sites. New methods of data fusion also need continued development if they are to be more widely used by non-specialists. Another continuing challenge is to increase communication and cross-fertilization across the many disciplines involved in human–landscape systems. Integrating qualitative approaches with quantitative methods is one example that could pay high returns in increasing the depth of our understanding of human–landscape systems.

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