Available online at www.sciencedirect.com
ScienceDirect
Geoforum 39 (2008) 805–818
GEOFORUM
www.elsevier.com/locate/geoforum

Exurbia from the bottom-up: Confronting empirical challenges to characterizing a complex system

Daniel G. Brown [a,b,*], Derek T. Robinson [a,b], Li An [c], Joan I. Nassauer [b], Moira Zellner [a,d], William Rand [a,e], Rick Riolo [a], Scott E. Page [a,f], Bobbi Low [b], Zhifang Wang [b]

[a] Center for the Study of Complex Systems, University of Michigan, United States
[b] School of Natural Resources and Environment, University of Michigan, United States
[c] Department of Geography, San Deigo State University, United States
[d] College of Urban Planning and Public Affairs, University of Illinois at Chicago, United States
[e] Northwestern Institute on Complex Systems, Northwestern University, United States
[f] Departments of Political Science and Economics, University of Michigan, United States

Received 21 February 2006; received in revised form 4 December 2006

Abstract

We describe empirical results from a multi-disciplinary project that support modeling complex processes of land-use and land-cover change in exurban parts of Southeastern Michigan. Based on two different conceptual models, one describing the evolution of urban form as a consequence of residential preferences and the other describing land-cover changes in an exurban township as a consequence of residential preferences, local policies, and a diversity of development types, we describe a variety of empirical data collected to support the mechanisms that we encoded in computational agent-based models. We used multiple methods, including social surveys, remote sensing, and statistical analysis of spatial data, to collect data that could be used to validate the structure of our models, calibrate their specific parameters, and evaluate their output. The data were used to investigate this system in the context of several themes from complexity science, including have (a) macro-level patterns; (b) autonomous decision making entities (i.e., agents); (c) heterogeneity among those entities; (d) social and spatial interactions that operate across multiple scales and (e) nonlinear feedback mechanisms. The results point to the importance of collecting data on agents and their interactions when producing agent-based models, the general validity of our conceptual models, and some changes that we needed to make to these models following data analysis. The calibrated models have been and are being used to evaluate landscape dynamics and the effects of various policy interventions on urban land-cover patterns.

Keywords: Urban sprawl; Land-cover change; Land-use change; Spatial modeling; Ecological effects

1. Introduction

One of the most dramatic changes on the landscape of the Eastern United States in the last 50 years has been the fivefold increase in the area of land settled at exurban densities (Brown et al., 2005a). This dispersed pattern of land development at and outside the fringe of urban areas has a range of effects on the functioning of ecological systems, through alterations in land-cover types and patterns (Brown et al., 2000), surface hydrology (e.g., Groffman et al., 2003), terrestrial habitat quality (Hansen et al., 2005), and material and energy flows such as carbon sequestration (Pickett et al., 2001). Understanding these land-use and land-cover patterns and the processes that give rise to them is important for managing landscapes to minimize negative ecological effects and enhance positive ones in the future. Importantly, because human–environment interactions are complex, achieving that understanding requires analysis of a whole system of interactions. The

* Corresponding author. Address: School of Natural Resources and Environment, University of Michigan, 440 Church Street, Ann Arbor, MI 48109-1041, United States.
E-mail address: danbrown@umich.edu (D.G. Brown).

0016-7185/$ - see front matter © 2007 Elsevier Ltd. All rights reserved.
doi:10.1016/j.geoforum.2007.02.010

research reported in this paper seeks to understand the interactions of human and social processes and land-cover dynamics at and beyond the urban–rural fringe and how complex dynamics affect these interactions. Ultimately, the outcomes of interest are the measurable biophysical landscape changes, but the explanations rest on the more elusive interplay between humans and that same landscape.

Our research draws on a number of theoretical and methodological themes from complexity science and the study of complex adaptive systems (CAS), which are essential foundations for biocomplexity studies. We use the term CAS to refer to systems that have (a) macro-level patterns (i.e. aggregation), (b) autonomous decision making entities (i.e., agents); (c) heterogeneity among those entities; (d) social and spatial interactions that operate across multiple scales; and (e) nonlinear feedback mechanisms (e.g., Axelrod and Cohen, 2000; Holland, 1995; Waldrop, 1992). Reviews of these and other complexity science themes and their relevance to geographical research have been well done by Manson (2001), O'Sullivan (2004), and Manson and O'Sullivan (2006). Rather than proposing a set of hypotheses to be tested (e.g., as a theory) or making specific ontological claims, the array of complexity science themes offer a flexible ontology based on things (or actors) and their relationships and makes epistemological claims about how we can learn about systems using, primarily, simulation modeling. In this paper, we use these themes to illustrate how empirical research has complemented simulation modeling in our biocomplexity research, by documenting system outcomes of interest, by parameterizing mechanisms encoded in models with data from Southeastern Michigan region, and by responding to empirical questions raised in the model development process.

We view exurban land-use change as an aggregate outcome (Manson, 2001) that results from the interactions of multiple actors, with each other and with the landscape, and that produces the observable spatial and temporal patterns of settlement and land cover. In our view the *primary* set of actors affecting land-use and land-cover patterns at the urban–rural fringe include the households that purchase residential properties, the developers that make these properties available to consumers, the farmers who use the land for agriculture, and the local governments (including their planning commissions and township boards) that regulate these transactions and provide infrastructure for the new developments. *Secondary* actors also contribute to this process by affecting the availability of credit (lending institutions), broader sets of infrastructure like the interstate highway system (federal government), and environmental regulations like those governing wetlands (state and federal governments). In order to focus our attention on the effects of land-use changes on the physical landscape, and because of the importance of local governments in setting land-use policy in the United States, we focused on the primary actors, while recognizing that the others also play a role.

Because landscape characteristics (e.g., landscape aesthetic quality) and location relative to urban amenities play a role in land-use decision making, and because those characteristics are subsequently affected by residential locations, simple uni-directional models (i.e., in which humans affect the landscape, but not vice versa) are inadequate. Feedbacks can be the essential ingredients that create complex nonlinear dynamics and that can complicate scaling from knowledge of agent behavior to understanding system behavior, like overall landscape patterns (Alberti, 2005). While a number of spatial land-use modeling frameworks exist in economic geography and regional science (Briassoulis, 2000), only rarely do these models consider landscape aesthetic characteristics or operate at scales that would permit representation of the interactions between land development and landscape patterns. Moreover, while many models of landscape aesthetic preferences can be found in the landscape architecture, environmental psychology, and cultural geography literatures (Nassauer, 1995; Daniel, 2001), these models rarely explicitly anticipate effects of changing aesthetic quality on urban land-use change. Agent-based models have allowed us to represent the actors in this system and their interactions, and to simulate landscape dynamics under multiple scenarios. Spatially explicit agent-based models (ABMs) have become popular tools for understanding land-use systems (Polhill et al., 2001; Parker et al., 2003; Deadman et al., 2004), but only a few have included these aesthetic feedbacks (Irwin and Bockstael, 2004; Parker and Meretsky, 2004). An agent-based model consists of a set of computational objects, called agents, that interact in space and time according to a set of rules. These agents can follow fixed behaviors, e.g., buy the nearest piece of land, or they can adapt their behavior, e.g., search k parcels and choose the best, where the parameter k changes over time in response to some feedback to the agent. These models produce system-level outcomes from the bottom up (Brown, 2005; Page, 2005). A pressing challenge in using these models to support understanding and scenario development is to link them more closely with empirical research (Janssen and Ostrom, 2007).

While computer models necessarily generalize a given process, and are the products of theory, empirical data refer to characteristics of specific cases (Brown et al., 2005c). Referring to a fundamental tension in complexity research between focusing on general system characteristics and specific examples of actors within the system, Manson and O'Sullivan (2006, p. 682) point out that "researchers walk a fine line between holism and reductionism". The mechanisms that support understanding a complex system are at the micro-level (i.e., reductionism), even though the goal of the analysis and modeling is to understand a system or macro-phenomenon (i.e., holism). By using real-world measurements to support the various processes encoded in the models, we hope to better represent the processes that give rise to observable patterns of land-use and land-cover. "A fuller understanding of the relationship between pattern and process ... seems most likely to be arrived at by relatively abstract modeling of spatial systems combined with considerable empirical grounding" (Manson and O'Sullivan, 2006, p. 685).

Although any given model of a particular system can be criticized as incomplete, as they certainly all are, we argue that the process of building simple representations of systems can help us understand the implications of our conceptual models and to identify areas where we need to learn more. By formalizing our conceptual models as computational models we uncover specific empirical needs answerable with traditional observational approaches. The results of our empirical investigations can then be used to calibrate the essential mechanisms in our computational models and discover alterations that must be made to the initial conceptual model. We are therefore describing an iterative process of conceptual model formation, parallel efforts of empirical analysis and agent-based (i.e., computer) model building, and conceptual model refinement, but focusing on the roles of empirical observations in the process.

This paper focuses on the empirical activities that have supported our modeling work aimed at understanding exurban land-use and land-cover change in Southeastern Michigan. We structure the discussion of empirical activities around several key theoretical themes that are used in complexity science: (a) macro-level patterns, (b) the autonomous decision making entities (i.e., agents); (c) heterogeneity in agents and the environment; (d) interactions that are structured socially and spatially and operate across multiple scales; and (e) feedbacks. The remainder of the paper discusses, first, our conceptual models based on expert opinion and preliminary pattern analyses. We focused on two of the key decision makers structuring demand for developed land in exurban landscapes, i.e., residents and land developers. We then formalized our conceptual models as pilot ABMs to help us identify our empirical needs, but leave out a detailed discussion of these models to place emphasis on the empirical work. Next we describe our empirical research that has been focused on (1) quantifying the macro-patterns of land-use and land-cover change that we want to understand using remote sensing based measures; (2) quantifying the behavior and heterogeneity in the actors and the landscape, and (3) defining the interactions among agents and between agents and the landscape. Finally, though feedbacks can be thought of as a type of interaction and can be the direct result of interactions in a model or system, we discuss separately our attempts to identify feedbacks within this system. We discuss the findings with respect this particular system, and the general implications of an approach to understanding complex systems that iterates between modeling and empirical observation.

2. Study area

Our study focuses on the 10 counties in Southeastern Michigan that comprise the Detroit, Ann Arbor, and Flint metropolitan areas. This is an excellent region to study land change at the exurban fringe. The region was home to about 5.5 million people in 2000. Although the total number of households residing in the four major cities of the region (i.e., Detroit, Flint, Ann Arbor, and Pontiac) declined from 494,374 to 455,099 between 1990 and 2000 – Ann Arbor was the only one of these cities that experienced an increase in the number of households – the number of households in the ten-county region increased from 1.92 million to 2.08 million over the same period (US Bureau of the Census, 2001). This disparity reflects a general deconcentration of the population within the region during the 1990s. At the same time (1992–2002), the amount of cropland in the region declined from 1.32 million acres to 1.25 million acres (US Department of Agriculture, 2002).

3. Two conceptual models

We started by building two conceptual models to represent key processes hypothesized to produce observable patterns of land use and land cover, and to guide the construction of computational agent-based models and the collection of empirical data. The models were based on theoretical considerations about relevant actors in the system, their interactions, and nonlinear dynamics that might emerge through feedbacks in the system.

3.1. A model of the urban system

Our first model focused on the role of locational preferences of residential households in determining the spatial patterns of development in and around a city center. We call the model SLUCE's Original Model for Exploration (SOME). The model also includes service centers that locate near recent residential in-migrants after a minimum number of new residents has entered. The inclusion of service centers captures a positive feedback between residential development and urban service provision: residents draw service centers, and service centers, in turn, attract residents. Residents or service centers locate in cells on a lattice; only one agent is permitted per cell. The residential agents use a boundedly rational decision making approach (Arthur, 1994) to select the cell at which to locate. In a model based on perfect rationality, residents would select sites from among all available locations and select the site that optimizes their utility. Our model assumes that residents optimize a utility function that includes distance to service centers and aesthetic quality as critical components, but their rationality is bounded by incomplete information about the real estate market (Brown et al., 2004; Brown and Robinson, 2006). The utility function the agents use is a variation of the Cobb–Douglas utility function (Chiang, 1984) and takes the following multiplicative form:

$$u_{r(x,y)} = \prod_{i=1}^{m} (\gamma_{i(x,y)})^{\alpha_{ir}} \quad (1)$$

where $u_{r(x,y)}$ is the utility of location (x, y) for resident r; α_{ir} is the weight the resident r places on factor i; $\gamma_{i(x,y)}$ is the value of factor i at location (x, y), and m is the number of factors evaluated (in our initial models, $m = 2$, distance to service centers and aesthetic quality).

Access to services is a critical component of the utility function, reflecting the longstanding tradition of modeling land change as a function of access to markets and jobs (Briassoulis, 2000). Existing empirical literature supports this tradition and shows that road patterns are critical for determining patterns of settlement (e.g., the hedonic analysis of Boarnet and Chalermpong, 2001). Some land-use models (e.g., DUEM; Batty et al., 1999) include road building as an endogenous feedback process. Road building affects and is affected by settlement patterns. However, we assumed that the bulk of the road system in Southeastern Michigan was established either before or very early in the period of interest (i.e., 1960–2000). While road capacity has surely changed, we assumed that the spatial pattern of the road network, which we believe is an important determinant of the pattern of settlement, was relatively stable. For this reason, we ignored the road system in cases where we modeled hypothetical landscapes, basing access calculations on Euclidean distance, and used a static representation of the road network from most recent data to calculate distances in cases where our models were intended to represent real places (Brown et al., 2005b).

The SOME model used either designed landscapes with assumed patterns of aesthetic quality (Brown et al., 2004), or maps of aesthetic quality for areas of Southeastern Michigan based on (a) relief – greater variations in which relate to more aesthetic quality; (b) land cover – more forest cover and other open space increases aesthetic quality; and (c) water – greater proximity to open water increases aesthetic quality (Brown et al., 2005b). A feedback is implicit in this simple definition of aesthetic quality. As development changes land-cover it, therefore, affects aesthetic quality for subsequent residents.

We implemented this model using Swarm (http://www.swarm.org) and explored its dynamics in the absence of empirical data to (a) compare the functioning of the model with an analytical model of the effects of a greenbelt near a growing city (Brown et al., 2004); and (b) demonstrate that the decision making of agents in the model can generate distributions of developed cluster sizes that compare well with the structural form of real-world cities (Rand et al., 2003). Furthermore, the model has been used to demonstrate new techniques for spatial model validation that recognize the possibilities for path dependence in the agent-based models (Brown et al., 2005b).

3.2. A model of an exurban township

Our second conceptual model focused on the evolution of land cover as residential development expands within exurban townships, and includes agents that represent township policy boards, developers, farmers, and residents that interact at a number of different scales. We call this model Dynamic Ecological Exurban Development (DEED). Developers assess township- and farm-level characteristics before making heuristic decisions about where to develop a specific type of subdivision. Residents decide where to locate by assessing environmental characteristics of lots within subdivisions. Different types of subdivisions have differential appeal to residents and differential effects on the land cover. The model consists of four agent types (farm households, resident households, developers, townships) and three spatial-object types (farms, subdivisions and lots). Agents in the model have their own behavior; objects may be created, used, or eliminated by agents in the model but do not have their own behavior.

A township (representing an area of about 9350 ha) is divided into farms, using either a regular grid pattern or a GIS-based map. Farmers create and offer for sale rural lots (Table 1) on some parts of their farms that are both (a) near county roads; and (b) on poor quality soil. Farms are then made available for sale with some probability each year. Farms are labeled as suitable for one or more of three subdivisions types–country, horticulture, and remnant—depending on their environmental characteristics (Table 1). Each subdivision type has a minimum lot size and a set of location rules. The developers determine if they are available to create a new subdivision. Developers may be constrained by a minimum lot size policy enforced by a township. In our conceptual model, minimum lot-size regulations favor higher-priced homes with lots that are more likely to contain natural features. Additionally, developers respond to demand from residents for particular types of lots. If a developer builds a subdivision of a given type and a threshold percentage of lots remain unsold, there are reasons to believe that they would be unable or unwilling to obtain financing for another subdivision of the same

Table 1
Residential development types in our expert conceptual model

	Lot sizes	Effects on Tree cover	Locations
Country subdivisions	Smallest	Decline	Are developed where there is no change in elevation, no water, and no forest
Horticultural subdivisions	Medium	Constant	May be developed in any location regardless of environmental amenities
Remnant subdivisions	Largest	Increase	Are developed where variation in elevation, water, or forest exists
Rural lots	Most variable	Decline	Near county roads and on non-prime soil

Each of these characteristics is subjected to threshold values (30%, 1%, and 10%, respectively) that govern the required amount to signify their existence at a location. These thresholds and assumptions govern development behavior for farms greater than or equal to 160 acres, other heuristics apply for smaller sized farms or rural lot developments.

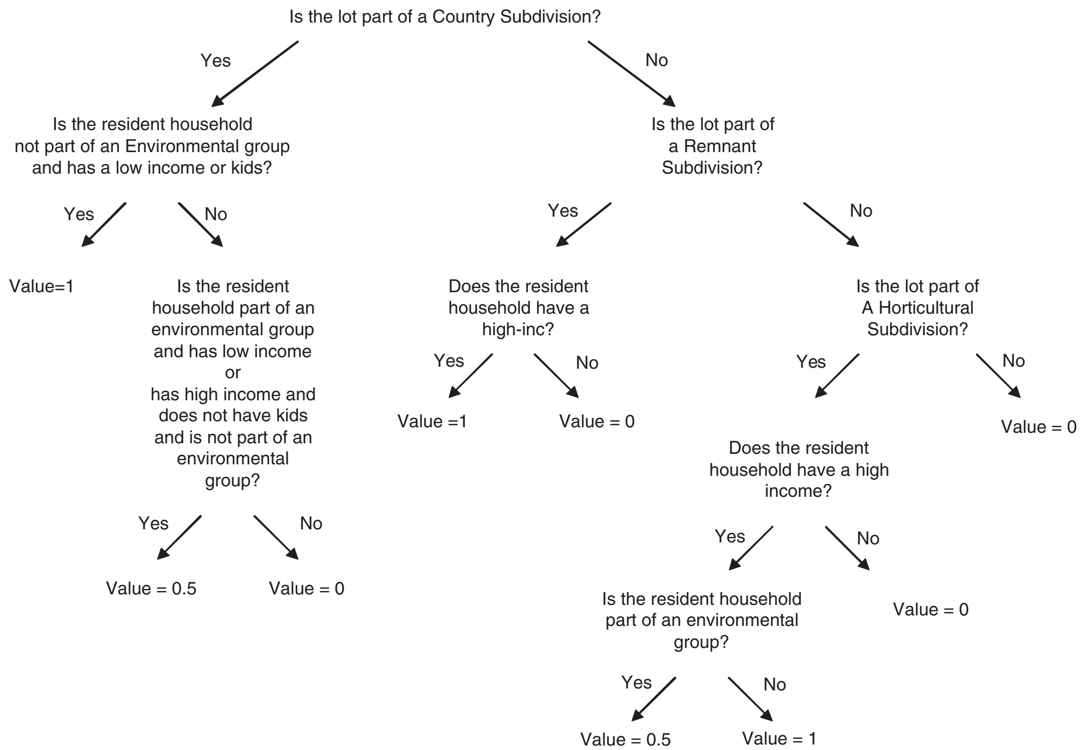

Fig. 1. Heuristic decision tree used by resident agents to evaluate the social and landscape characteristics of a subdivision.

type. If available, the developer develops the lots within the subdivision and offers them for sale to residents.

Residents enter the model at a constant rate (e.g., 10 per time step) and have variable preference weights for environmental characteristics and heuristics describing which subdivision type they prefer. Both preference weights and subdivision choices are determined by their socioeconomic characteristics, including income, parental status, and whether or not they belong to an environmental group. Membership in an environmental group is included as a lifestyle indicator, recognizing that choices are not wholly determined by life-stage factors. Residents randomly select lots in a number of subdivisions for evaluation and move into the most suitable subdivision or exit the model if no suitable lot can be found (e.g., there are no available lots or they are unaffordable). The utility calculation for residents is as follows:

$$\text{Resident\_Utility}: = \frac{\alpha_{\text{forest}} \cdot \text{sub}_{\text{farea}} + \alpha_{\text{pv}} \cdot \text{sub}_{\text{pv}} + \alpha_{\text{relief}} \cdot \text{sub}_{\text{relief}} + \alpha_{\text{water}} \cdot \text{sub}_{\text{warea}}}{4} \cdot \text{Subdivision\_Evaluation} \quad (2)$$

where the α's are the resident's preference value for forest, panoramic view (pv), change in relief (relief), and water. The *sub* variables are the subdivision environmental feature values that correspond to the resident preferences (area forest – farea, area water – warea, others as listed above). The last term *Subdivision_Evaluation* represents a heuristic decision tree that determines the resident's evaluation of a subdivision based on its type and his/her socio-economic characteristics (Fig. 1). All values in the utility equation are scaled to a range of 0.0–1.0.

Each cell in the landscape begins with an initial amount (proportion) of tree cover. The tree cover is modified over time, according to the type of development that occurs. If the cell is part of a country subdivision or a rural lot, all trees are removed. If the cell is part of a horticultural subdivision, the trees remain unchanged. If the cell is part of a remnant subdivision, the tree cover is incremented in all cells until the total tree cover in the subdivision is 20%, or until the tree cover is 20% higher than it started with, whichever amount is greater. These landscape changes reflect the relative effects we expect the subdivisions to have on tree cover. The initial regrowth rates were set to reflect our understanding of tree-cover patterns within subdivision types.

With this model we have explored (a) the interactions between public and private lands in creating habitats of various kinds, focusing mainly on tree cover, in exurban regions; and (b) the payoffs to townships seeking to plan for an increased tax base, in the form of more and wealthier residents, and increased ecological quality, in the form of increased tree cover (Zellner et al., in review). Running the model with two adjacent townships, each with the ability to set their own lot-size regulations, reveals the types of policy games that can emerge as townships independently seek their own payoffs within a regional context.

4. Empirical elements of complexity

4.1. Macro-level patterns

An analysis of a complex system often begins with patterns in space and/or time that are difficult to explain with simple linear relationships. Our project focused on both the spatial patterns of land development, the subsequent effects on land-cover proportions, and the temporal trends in those proportions. We use these observations as indicators of the ecological effects of land change.

To describe the land-use and land-cover changes that have occurred outside the core urban areas in Southeastern Michigan, we compiled data on the land-uses of parcels and the proportional composition of these parcels in multiple land-cover classes (i.e., tree cover, impervious surface, agriculture, other-natural covers) within selected townships between 1950 and 2000. We selected 13 townships for analysis and to represent a range of conditions with respect to the amount and timing of population growth and development. Land-owner parcels within the townships were digitized from plat books compiled in the late 1950s, 1960s, 1970s, 1980s, and 1990s (Rockford Map Publishers, 1956–1999). Land-uses and land-covers were interpreted for each parcel by overlaying parcel boundaries on aerial photographs that were selected from the nearest available date (a maximum 2-year difference) to the parcel maps and scanned at 2 m resolution.

Based on data from 11 of our 13 sample townships (those for which sufficient data were available), tree cover increased in our sample townships by an average of 1.8% (or 29 ha) per year between the mid 1950s and late 1990s (the range across the 11 townships was from +0.4% to +3.5% per year). Because of the location of the region within the Eastern temperate forest zone, increasing tree cover is a possible indicator of ecologically beneficial landscape changes. However, impervious surfaces also increased, by an average of 11.1% (or 28 ha) per year (ranging from −3.3% to +26.2% per year). Because of decreased groundwater recharge, increased runoff, and consequent potential for surface water pollution, such increases can indicate negative ecological effects. These increases were largely at the expense of agricultural land covers, which declined an average 1.5% (or 70 ha) per year (ranging from −2.9% to −0.04% per year). It is these landscape changes, as well as their effects on spatial patterns, that we seek to understand through modeling.

The trajectories of land-covers in three illustrative townships (Fig. 2) demonstrate the land-cover transitions the townships are undergoing. The three townships, Tyrone, Scio, and Rochester, are representative examples of townships with low (9 people/10 ha), moderate (23 people/10 ha) and high (83 people/10 ha) levels of population density in 2000, respectively. They each demonstrate a steady decline in crop cover and steady increase in impervious cover over a period of approximately 40 years. Crops are being replaced in large measure by trees and other land covers (including managed and unmanaged grasslands). Each of these cases suggests a phase transition in the amount of tree cover on the landscape. From a low level of tree cover associated with agricultural landscapes to a somewhat higher level associated with residential landscapes. Rochester has certainly completed that transition; and changes is tree-cover in Scio Township also appear to have slowed. Tree cover in Tyrone Township was increasing rapidly during the 1990s, indicating that township is in the early stages of this transition.

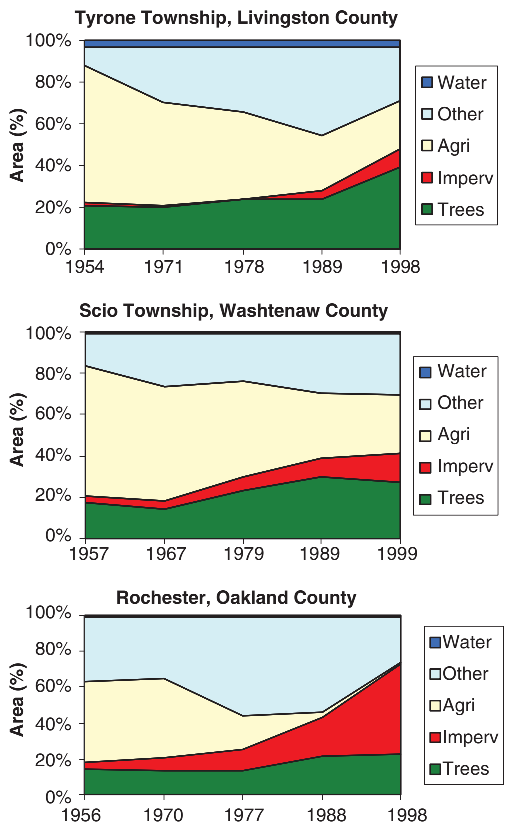

Fig. 2. Changes in proportions of land covers in three sample townships.

In addition to these changes in land cover, we have used spatial metrics of land-use and -cover patterns, for example using the approach taken in the Fragstats software (McGarigal and Marks, 1995), and maps that identify regions of invariant and variant outcomes from the models (Brown et al., 2005b) to provide multiple patterns for assessing the usefulness of the model for experimentation and scenario analysis. Following the pattern oriented modeling (POM) approach described by Grimm et al. (2006), we are interested in understanding how these spatial and temporal patterns in land use and land cover come about as a result of agent-level processes, and we have compared agent-based model output to multiple pattern descriptions to enhance our confidence in them (Rand et al., 2003; Brown et al., 2005b).

4.2. Micro-level decision making

The ways agents make decisions are central to determining the overall functioning of an agent-based system. Decision models specify what information the agents use and how they combine that information with their own preferences to decide which specific actions to take. They also determine how agents interact with each other and/or with the environment. In the SOME model, residential agents make decisions about where to locate themselves after gathering information about the characteristics (i.e., nearness to services and aesthetic quality) of a sample of sites and calculating a utility for each that combines that information with weights representing their preferences for certain characteristics (Eq. (1)). The DEED model includes developer agents that make decisions about where to locate developments of a given type based on the landscape and location characteristics of available farms. Residential agents then locate themselves within subdivisions using a utility calculation (Eq. (2)) that considers the physical landscape characteristics associated with different subdivision types.

4.2.1. Residential locations

Empirical support for the decision-making models can take many different forms (Robinson et al., 2007; Janssen and Ostrom, 2007). Empirical challenges include (a) evaluating if the structure of the decision model is correct; (b) assessing which factors and inputs the agents consider in making the decisions; and (c) determining the appropriate weights to assign for each agent and each factor (i.e., α_{ir}). We used survey data to answer the last two of these empirical imperatives, but did not evaluate the first.

For independent data on the distributions of residential preferences in the population of the region, we turned to survey research on residential preferences (Marans, 2003). The data were derived from household surveys conducted in the Detroit metropolitan area during the spring and summer of 2001. In part of the survey, each respondent was asked about the relative importance of factors influencing their decision to move to their current house. A four-point importance scale ranging from ''very important'' to ''not at all important'' was used for the following 12 factors: close to work; good schools; housing costs and good value; convenient to places such as shopping and schools, lots of recreational opportunities; attractive appearance of neighborhood; community size; people similar to me; appearance and layout of the dwelling; familiar with area; close to natural areas (woods, ponds, streams, etc.); openness and spaciousness of area; and close to family and friends.

We analyzed these data to evaluate the correlations among responses to the different factors (using factor analysis), the clustering of responses around particular patterns of responses (using cluster analysis), and the relationships between responses and characteristics of the households, e.g., education, income, race, marital status and age (Fernandez et al., 2005). The analysis was limited to respondents who had moved to an exurban location within the last ten years. *t*-tests (detailed by Fernandez et al., 2005) revealed the following relationships: having children under 18 in the household resulted in stronger preference for nearness to work and good schools, and weaker preference for residential aesthetic concerns; households headed by married couples had stronger preference for nearness to work and good schools; households with income greater than $75,000 had weaker preference for social comfort factors (e.g., near family and friends, familiar with area, people similar to me); and respondents over 40 years old had weaker preference for nearness to work and good schools. Neither college education nor membership in a minority group were significantly related to differences in stated preferences. Overall, the preferences of residents were only weakly related to the measured household characteristics, and these characteristics serve as only partial surrogates for location preferences. It is likely that additional lifestyle factors are needed to explain preferences, which is why we included membership in an environmental group in the DEED model.

To identify the relative importance of landscape factors in our conceptual model of homeowner decisions, which includes landscape characteristics at the regional, subdivision, and lot scales, we conducted a web-based choice experiment with 494 homeowners in Southeastern Michigan who lived in areas that were dominated by large-lot zoning as identified by municipal boundaries. This web-based survey invited homeowners to ''shop'' for a new home, neighborhood, and yard within the price range of the home they currently owned. It presented a range of ecologically beneficial and conventional designs for subdivisions and finer-scale residential development features (e.g., open spaces, streets, and yards) and allowed respondents to choose their most preferred new house within a large-lot exurban residential development. Survey respondents also provided information on other demographic and behavioral variables that we believe are potential correlates with landscape preferences across scales.

The web-based survey results indicated that increased neighborhood tree cover is positively correlated with homeowner preference in new exurban subdivisions, accounting for 52.1% of variance in preference for neighborhoods and for 56.2% of variance in preference for residential streets. Responding to views of exurban open spaces, homeowners strongly disliked large areas of turf, including athletic playing fields, and preferred wooded areas; these two factors together accounted for 74.6% of variance in preference for views of exurban open spaces. These results support Eq. (2), which demonstrates that those who can afford to do so would prefer to live in wooded exurban subdivisions near forested open spaces, like the more expensive remnant subdivisions in the conceptual model.

Although survey data can provide valuable information about the distributions of agent characteristics, and of stated preferences, they provide no indication of the processes by which agents make decisions. In our simple agent-based model, we assumed that all residents optimize a utility function that was of the same form for each agent. The nature of this utility function, and the ways in which agent rationality is bounded, are elements of our conceptual model that remain to be tested against empirical or experimental cases. Hedonic price models can reveal parameters that describe variations in price, and can be used to infer variations in agent preferences (e.g., Geoghegan et al., 1997), but they are similarly challenged to provide justification for the structural form of the utility function. Although we have used sensitivity tests to evaluate the implications of different utility models (Rand et al., 2002), additional work, using field and lab experiments for example, is needed to evaluate how residents actually decide, and how heterogeneous are the ways people actually make land-use and land-cover decisions (Evans et al., 2006).

4.2.2. Subdivision locations

Initially our conceptual model used heuristics, informed by expert opinion, to describe how the development types are located on the landscape (Fig. 1, Table 1). We operationalized the conceptual model as a pilot ABM, i.e., DEED. We then empirically evaluated the location of development types by testing the relationships between development events and locational attributes, including environmental, geographical, and socio-economic variables (An et al., submitted for publication). The environmental variables we measured for each sampled subdivision were soil quality, slope, and initial tree cover (i.e., that observed in the decade before the subdivision was built). The geographical variables included distances to the nearest city in each of three hierarchical levels (Detroit, five mid-level cities, and small urban areas), along with distances to nearest water feature (i.e., lake or river), highway, and county road. All of the environmental and geographical variables were measured at the most recent time for which data were available. The time-varying socio-economic characteristics of townships in which each development fell were collected from US census data. Factors measured for each decade and each township included population density, population change rate, median age, and education level.

We used survival analysis to understand relationships between development of each type and the explanatory variables. An important advantage of survival analysis is its ability to account for time-varying factors that affect establishment of the development types and the inherent inaccuracy in measuring the timing of the events. A survival model takes the following general form:

$$\log h_i(t) = \alpha_i(t) + \beta_1 X_{i1}(t) + \beta_2 X_{i2}(t) + \cdots + \beta_k X_{ik}(t) \quad (3)$$

where $h_i(t)$ is the time-varying hazard rate (instantaneous risk of being developed at a time) for parcel i, $X_{ik}(t)$ is the value of explanatory variable X_k for parcel i at time t, and β_k are the coefficient values for the kth variable. In addition, β_k can vary if an interaction term with time is added in the model.

The analysis results confirmed several aspects of the conceptual model regarding placement of developments of different types (Table 2). Results of the survival analysis supported our assumptions that the prevalence of remnant subdivisions tended to increase with distance from county roads, higher initial tree cover, higher slope, and proximity to Detroit and five mid-level cities. As time went on, remnant subdivisions occupied land of increasingly good soil. Horticultural subdivisions were more likely to be located in areas closer to the five mid-level cities and became increasingly proximate to Detroit over time. Country subdivisions tended to be near county roads and far from

Table 2
Effects of landscape variables on the location of subdivision developments

	Unit	Country subdivision			Horticultural subdivision			Remnant subdivision		
		DEED Pilot Model	%Δ in hazard rate per unit Δ	Scaled alpha values	DEED Pilot Model	%Δ in hazard rate per unit Δ	Scaled alpha values	DEED Pilot Model	%Δ in hazard rate per unit Δ	Scaled alpha values
Distance from county roads	1 km	Strong negative	**−0.65**	0.00	No influence	−0.21	−0.04	Positive	0.13	0.00
Distance from water	1 km	Positive	**164.34**	0.60	Negative	24.24	4.62	Negative	46.69	0.39
Percent tree cover	1%	No influence	0.93	0.00	Positive	−2.06	−0.39	Strong Positive	**1.26**	0.01
Soil quality (prime farmland)	0 or 1	N/A	48.55	0.18	N/A	−3.05	−0.58	N/A	**69.67**	0.58
Percent slope	1%	Strong negative	**60.65**	0.22	Positive	−12.81	−2.44	Positive	**8.49**	0.07
Distance from 5 city centers	1 km	N/A	−2.13	−0.01	N/A	**4.74**	0.90	N/A	**−3.18**	−0.03
Distance from Detroit	1 km	N/A	2.64	0.01	N/A	**−5.60**	−1.07	N/A	**−2.64**	−0.02

water. They were located on good soils at early time periods, but this soil effect diminished over time.

Using the hazard-rate equations for the development of each subdivision type, we extracted the relative difference and direction of influence of each independent variable on the hazard rate. Then we rescaled these relative weightings to empirically inform the preference weights in a utility function used by developer agents to evaluate farms for subdivision. Using the same form as Eq. (1), the independent variables are weighted using the scaled values listed in Table 2. It should also be noted that the survival analysis identified three variables of influence (i.e. soil quality, distance to five mid-level cities, and distance to Detroit) that were not included in the conceptual or pilot models, but were significant for identifying the location of at least one of the subdivision types. Because the DEED model was implemented at the township level, the township variables that had been included in the survival model were not used in the computational model.

Though our empirical analysis does not confirm that the factors used in the statistical model were, in fact, those considered by developers, it provides evidence that the development process results in the development types being spatially distributed in ways that our conceptual model suggests. Furthermore, the identification of additional variables of significant influence from our empirical analysis supports the need for modeling to be an iterative process and refinement of conceptual design, empirical data collection, and model construction.

4.3. Heterogeneity

Systems composed of multiple agents that interact to create feedbacks can be very sensitive to the actions of a small number of agents that have particular characteristics. For this reason, understanding the actions of average agents is insufficient to explain observed patterns and it is important to understand the nature of heterogeneity among agents within a system. To better understand the implications of the heterogeneity found in human systems, more researchers are using agent-based techniques (e.g. Parker et al., 2003). Because of their ability to both formalize heterogeneity to a degree that more closely parallels real systems and track or trace the behavior of an individual agent and/or group of agents, agent-based tools can better represent complex interactions among many heterogeneous actors than traditional mathematical models of land-use systems.

4.3.1. Resident preferences

To evaluate the effects of varying preferences on land-use patterns in the urban growth model, we used characterizations of heterogeneity of preferences from survey respondents directly, i.e., based on the factor analysis of Fernandez et al. (2005). The SOME model was run with agents having varying degrees of heterogeneity in preferences, including the following cases: (1) no heterogeneity (i.e., homogeneous agents); (2) normal distributions of preferences describing the factor scores that were based on the survey results; (3) mean preferences for seven groups or clusters, identified from cluster analysis of the survey data; (4) seven different normal distributions of preferences representing variability within each of the seven clusters; and (5) uniform random distributions, set up with no information from the survey as a null model for comparison. Results of model runs that included the heterogeneous resident preferences, whether drawn from the survey or drawn randomly, exhibited more sprawling and fragmented patterns than did runs of the same model with average agent preferences; and agents were able to achieve higher levels of average utility when their preferences varied (Brown and Robinson, 2006). These patterns can be attributed to the importance of residential agents with a very strong preference for aesthetic quality, relative to other factors, and the feedbacks in our model that involve stochastic placement of service centers to serve existing residents. The sensitivity of the results to heterogeneity supported our assumption that agent-based models would be helpful in understanding land-use systems.

4.3.2. Differentiation of development types

Our residential development typology defines four types of exurban lots or subdivisions, each of which was defined by observed land-cover proportions and patterns, street patterns, and lot sizes. We hypothesized that these types were different in terms of the effects they had on land-cover changes, and therefore subsequent ecological effects. The heterogeneity of these ecological effects is one mechanism by which landscape patterns can be determined by agent level actions. Empirical tests of the observed land-cover changes associated with each type constitute a partial validation of the typology and of these mechanisms.

To test land-cover change impacts of developments, we used to parcel maps obtained from eight townships, together with recent aerial photographs, to identify subdivisions and label their type. We sampled approximately 4% of the parcels in these townships ($n = 854$). Parcels were merged to form larger polygons representing subdivisions. Using the historical aerial photographs, we recorded the land-cover characteristics within these polygons, focusing on percent tree cover, in each decade between the late 1950s and late 1990s and also identified the decade during which each subdivision was started.

For a stratified random sample ($n = 427$) of subdivisions, we found significant differences between development types and the proportional change in tree cover and other natural cover. For each of the subdivisions, we measured the tree-cover percentages in the images taken immediately before the development and the average (over decades) percentages after the development, and then we did a series of two-sample *t*-tests. We found that tree cover of a location tended to increase after development of remnant subdivisions ($p < 0.05$ for null hypothesis that the percentages before and after developing into remnant subdivisions are equal). There was some, but less consistent, evidence that tree cover tended to decrease after development of country subdivisions ($p < 0.05$ for the same null hypothesis), while no significant change in tree cover was found in horticultural subdivisions ($p = 0.30$). This analysis substantiated the directionality of our assumptions about the differential landscape effects of subdivisions that we had represented in the DEED model, in which tree cover increased for remnant subdivisions, decreased for country subdivisions, and stayed constant for horticultural subdivisions.

4.4. Interaction

Interactions between agents can include the means by which they communicate with each other or the effects of one agent on the environment (e.g., landscape), which can affect the subsequent actions of other agents. Our models included a variety of interactions for which we attempted to collect empirical data. The interactions between developer and residential agents in the DEED model operate across scales and were affected by the indirect effects of developments on landscape characteristics (described above), but also by the effects of costs of developments on the ability of residents to pay for the lots they prefer. We validated these latter interactions by examining differences in housing price within subdivisions in Southeastern Michigan that we had labeled as remnant, horticultural, or country subdivisions. Our analysis of the survey data on residential preferences highlighted the potential importance of social interactions, which we examined with experiments using the SOME model. Finally, the rules governing the effects of development on tree cover in the DEED model raised questions about possible spatial interactions that were not accounted for in our simple rules for tree-cover effects based on subdivision type alone. We sought to answer these questions with remotely-sensed data on the spatial patterns of tree-cover effects by subdivision.

4.4.1. Cross-scale interactions

In the empirical test of market valuation, we examined a sub-sample of these subdivisions ($n = 826$), and looked at the assessed market valuation of individual properties within the subdivisions. We constructed a regression model to evaluate the factors that relate to the market value of homes (as the dependent variable). Included as independent variables were house size, lot size, house age, and dummy variables for the type of subdivision the house was in (i.e., country, horticultural, and remnant subdivisions). Controlling for the other variables, development type was a significant predictor of the market valuation of homes, predicting 8.4% of the variance in standard equalized valuation ($p < 0.000$). House size was nearly seven times more important in the model, while lot size and house age were about 1.5 times as important. Houses in remnant subdivisions were significantly more expensive, holding other factors constant, than houses in the other types of subdivisions. This cost effect is compounded by the fact that remnant subdivisions tended to contain larger houses on larger lots than the other types. This empirical test supported the validity of our assumption that residents' selection of different types of developments would be influenced by the wealth of the agents.

4.4.2. Social interactions

Our initial conceptual and computational models of SOME incorporated only aesthetic quality and distance to service centers as landscape attributes influences residential location decisions. Results from our analysis of the survey suggested that residents also used a third factor in deciding where to locate, which was labeled social comfort (Fernandez et al., 2005). Some agents heavily weighted their location decision based on such characteristics as if the location was near family and friends, if a neighborhood was populated by people like themselves, and if they were familiar with the area. As a result of this analysis, we modified our conceptual model and the corresponding agent-based model to include a consideration of neighborhood similarity as a factor in the utility function (Eq. (1); Brown and Robinson, 2006).

4.4.3. Spatial interactions

The DEED model includes a representation of the land-cover effects of residential development, through changes in tree cover. It does not currently have explicit mechanisms for modeling the spatial patterns of tree-cover change, either within or among subdivisions. To develop such mechanisms, so that we can use the model to understand the spatial patterns and amount of tree cover, we have pursued two strategies. We have used the results of the web-based survey to evaluate the importance of spatial interactions in the land-cover decisions of residents, and the aerial photography to evaluate the spatial adjacency effects in the amounts of tree-cover within subdivisions.

The web-based survey included questions that allowed us to evaluate the effect of neighbors' landscape patterns on homeowners' preferences for their own landscapes. When selecting a specific design for their yard from among multiple alternatives, residents were shown simulations of what the yards of their neighbors would look like in their hypothetical home-shopping situation. The results indicated a strong effect of neighboring yards on residents' choices. Specifically, when respondents were shown neighboring yards that had conventional designs they preferred a conventional design for their own yard significantly more than any other yard design ($F = 42.73$, $p < 0.0001$). However, when respondents were shown that all adjacent neighbors' yards used innovative ecological designs, contrary to broad cultural conventions, respondents preferred an innovative design for their own yard significantly more than any other yard design ($F = 51.83$, $p < 0.0001$) (Nassauer et al., in preparation).

Though our analysis (described in the section on Differentiation of Development Types) demonstrated that the subdivision types had differential effects on the dynamics of tree cover that were consistent in relative terms with our hypotheses, implementing our conceptual model and evaluating its ecological landscape effects required that we also define the model in terms of the amount and pattern of land-covers resulting from different development types. To evaluate the differential effects of development on land-cover patterns, we used the aerial photos together with the parcel maps to quantify how the amount and pattern of land-covers were related to land-use types under various conditions. For example, the frequency of low-density residential developments in our 13-township sample decreases with increasing percent tree cover with a mean and standard deviation of 18.9% and 17.9%, respectively. Using such a distribution, the amount of tree cover can be assigned probabilistically by the agents using the land. The amount of land cover assigned through this method provides an initial estimate. Further refinement of this approach will require testing for adjacency effects, i.e., how land cover in a subdivision might be related to the land-covers of neighboring subdivisions, and whether these adjacency effects can be observed to change over time. Incorporation of adjacency effects can create the additional nonlinear feedbacks within the system. We plan to evaluate such effects using summaries from our land-cover data analyzed at the scale of subdivisions.

4.5. Feedbacks

Our conceptual models include a number of feedbacks that we believe are important in exurban land-change processes, including those between landscape aesthetic quality and residential and subdivision locations and designs and those between residential locations and the locations of urban services. These feedbacks are an important controls on the models of this system (as well as the system they represent), observed complex nonlinear dynamics, and sensitivity to both initial conditions and to small perturbations in the distributions of inputs (i.e., sensitivity to heterogeneity). We addressed the effects of landscape characteristics on residential preferences, an important form of feedback, in our web-based survey (described above).

A number of existing models address the important feedback between land-use change and transportation systems (Wegener, 2005). Our assumption of a static road network raised an important empirical question, about the degree to which the road network in the region had changed over our study period as a result of infrastructure investment. Using our compiled aerial photographs, we mapped roads in each decade using a classification system based on the National Functional Classification (NFC) system developed by the US Federal Highway Administration (US FHWA, 1989). We calculated the sum of the length of all roads across all 13 townships for each date and each class (Fig. 3). The most substantial increase in the length of principal, minor, or collector roads occurred between 1950 and 1960, with the creation of the interstate highways. After that period, the length of these road types increased by only 13%, 4%, and 10% from 1960s to 2000, respectively. Therefore, though the road system likely had a significant impact on settlement patterns, the roads that establish the accessibility of various locations on the landscape changed only a little after the initial decade of the last half of the 20th century. On the other hand, the lengths of local roads and, especially, residential roads increased quite dramatically over the entire period (155% from the 1950s to 2000). These increases, along with the widening and increased traffic on the major roads, may have directly affected both ecological systems (Forman et al., 2003) and accessibility within the urban system. Given our focus on townships in Southeastern Michigan between 1950 and 2000, this analysis supports our decision to treat the system of major roads and highways as exogenously determined, but points out that ecological effects associated with residential road building might, nonetheless, have been substantial.

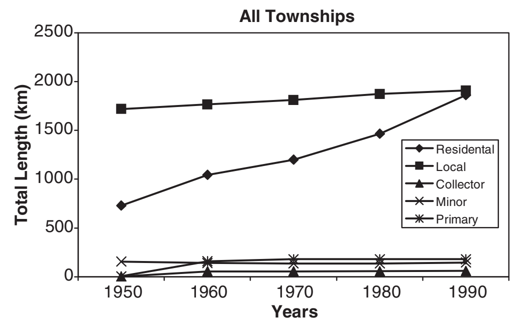

Fig. 3. Trends in road lengths by type of roads across 13 townships in Southeastern Michigan.

5. Discussion and conclusions

In order to characterize the dynamics of a system that couples human decision making about land use and land management at the urban–rural fringe with biophysical changes on the landscape, we have constructed conceptual models that take an agent-based view of that complex system. Our conceptual models incorporate a number of themes from complexity science, including: (a) macro-level patterns, (b) the autonomous decision making entities (i.e., agents); (c) heterogeneity in agents and the environment; (d) interactions that are structured socially and spatially and operate across multiple scales; and (e) feedbacks. The conceptual models have led us in two epistemological directions simultaneously. First, we have used and constructed agent-based computational models to represent key aspects of the system. These computational models force us to formalize our knowledge of the system and allow us to evaluate the implications of that knowledge in ways that other analytical approaches do not (Lempert et al., 2002).

Secondly, we present in this paper empirical data collected to describe both macro- and micro-level patterns and processes for the purposes of refining and validating our conceptual models as well as providing patterns to calibrate our computational models. The divergent nature of our empirical needs, described in this paper, has required us to employ a range of methods, including survey research, remote sensing, spatial analysis, and survival analysis. This work leads us to some general conclusions about the relationship between general models and specific places, as well as specific conclusions about our own conceptual models of land-use and land-cover change at the urban–rural fringe.

Our work suggests that the distribution of preferences and behaviors the various actors (e.g., residential land purchasers and developers) can have significant effects on the settlement patterns that result from the interactions of those actors. We have no evidence that the distributions vary from region to region, as our focus was exclusively on Southeastern Michigan, but we do find significant variation among actors in the region and, to the degree that the distributions of variation are different in different regions, we might expect differences in land-use dynamics and spatial patterns.

Variation in natural landscape characteristics might also be expected to influence settlement patterns and subsequent effects on landscapes and ecological processes. Our analysis identified four types of developments that we observe in exurban parts of Southeastern Michigan. One of these types, i.e., remnant subdivisions, is associated with the presence of environmental amenities that have the potential to provide environmental benefit. Because these subdivisions have significantly different effects on land cover from the other types (i.e., tree cover increased on these, but remained constant or decreased on the others), the abundance and spatial distribution of environmental amenities could have a significant influence on (at least the potential) patterns of development and their effects. Furthermore, although our analysis does not permit conclusions on this question, it is possible that the relative abundance of different development types, and even the types themselves, could be different in different regional settings, with different environmental amenities (e.g., mountains) and different planning environments (e.g., growth boundaries).

Our methodology is drawn from complexity science and focused on understanding the formation of aggregate, or macro-level, patterns from micro-level processes. To better understand the macro-level patterns, we collected data on the trajectories of land-cover change within 13 sample townships in Southeastern Michigan. Many of the townships have undergone in the last half of the twentieth century, or are still undergoing, a transition from predominantly agricultural land uses to predominantly residential. The transition is manifested in a steady, and sometimes rapid, decline in land covers associated with crops, a steady increase in impervious surface, and a phase transition in the amount of tree cover from a relatively low level to a somewhat higher level. The computational models we have built are intended to help us understand both the spatial patterns of settlement (in the case of SOME) and the amounts and distributions of tree cover (in the case of DEED) in exurban Southeastern Michigan.

Our empirical data collection about micro-level processes has focused on the decision making of and heterogeneity in the two primary actors, the residents who buy residential lots and the developers who build them (represented by types of developments). Our analysis generally confirmed several critical features of our conceptual models. First, residents consider both aesthetic quality and proximity to urban services and jobs in their selection of a residential location. Second, the relative importance residents' place of various location factors exhibits significant variability. Third, the four development types (i.e., rural lots, country subdivisions, horticultural subdivisions, and remnant subdivisions) were significantly different on dimensions that were relevant to our conceptual model, i.e., their biophysical landscape effects, and their locations were consistent with many of their hypothesized locational characteristics.

An important challenge that an agent-based view of systems creates for empirical data collection is in the identification and quantification of interactions among agents. Our empirical work uncovered social, spatial and cross-scale interactions that could prove significant for the functioning of our agent-based models. First, some residents indicated a great deal of importance of factors related to social comfort or similarity in choosing where to live (e.g., familiarity with the area, proximity to family and friends). Because of this empirical result, we subsequently included a social similarity factor into the SOME model. Second, our web-survey of landscape preferences revealed a strong spatial interaction, such that the preferences of individuals for the look of their own yards were significantly affected by the look of neighbors' yards. We have not yet incorporated this interaction into the DEED model, but plan to do so. Third, we hypothesize that similar spatial effects on landscape design will also be apparent at the subdivision scale, but have not yet completed data collection to test this. Finally, we identified ways in which different types of agents interact, e.g., through effects of subdivision types on price signals to residents.

Another empirical challenge raised by complexity science is in the quantification of feedbacks. Some of the feedbacks are built into the specific interactions represented in our models, for example in the way in which landscapes affect residential choices and residential choices affect landscapes. We also analyzed the spatial pattern of the road network to evaluate the possible importance of a missing feedback between the road network and land use patterns. After 1960, we observed large increases in residential streets and slight increases in major roads. While major roads clearly played a large role in establishing the pattern of development, this finding gives us some confidence that, though road capacities have surely changed, their spatial patterns were relatively well established by 1960. Note that this finding is likely to be regionally and temporally specific.

In addition to assisting the validation of our conceptual models, we used the empirical data collection to provide calibration of our models. This form of calibration differs from the more common approach of tuning the value of a parameter until the macro-scale patterns match observed patterns. We aim to calibrate the micro-level processes independently, to ensure that the process structure of our models most accurately represented the structural mechanisms in the target system. The surveys provide some calibration of the relative importance of various factors in the residential location. The survival analysis contributed to the calibration of factors that influence the location of different types of residential developments. The analysis of land-cover within land-use types from remote sensing provides calibration for the landscape effects (both quantity and location/pattern) of various land-use conversions. Empirically calibrating ABMs may facilitate the extension of ABM applications over relatively large geographic regions. ABMs are known to be data demanding, especially when used in real applications. Multi-method and creative approaches are needed to collect the data needed to calibrate these models.

Acknowledgements

We gratefully acknowledge financial support in the form of Grants from the National Science Foundation Biocomplexity in the Environment Program (BCS-0119804) and the Office of the Vice President for Research at the University of Michigan.

References

Alberti, M., 2005. The effects of urban patterns on ecosystem function. International Regional Science Review 28 (2), 168–192.

An, L., Brown, D.G., Nassauer, J.I., Low, B. submitted for publication. Timing, location and determinants of residential development types in exurban Southeast Michigan.

Arthur, W.B., 1994. Inductive reasoning and bounded rationality. The American Economic Review 84 (2), 406–411.

Axelrod, R., Cohen, M.D., 2000. Harnessing Complexity: Organizational Implications of a Scienctific Frontier. Free Press, New York.

Batty, M., Xie, Y., Sun, Z., 1999. Modeling urban dynamics through GIS-based cellular automata. Computers, Environment and Urban Systems 23 (3), 205–233.

Boarnet, M.G., Chalermpong, S., 2001. New highways, house prices, and urban development: the case of toll roads in Orange County, CA. Housing Policy Debate 12 (3), 575–605.

Briassoulis, H., 2000. Analysis of land use change: Theoretical and modeling approaches. Regional Research Institute, West Virginia University, Morgantown, WV <http://www.rri.wvu.edu/WebBook/Briassoulis/contents.htm>.

Brown, D.G., 2005. Agent-based models. In: Geist, H. (Ed.), Our Earth's Changing Land: An Encyclopedia of Land-Use and Land-Cover Change. Greenwood Press, Portsmouth, NH.

Brown, D.G., Robinson, D.T., 2006. Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl. Ecology and Society 11 (1), 46 <http://www.ecologyandsociety.org/vol11/iss1/art46>.

Brown, D.G., Pijanowski, B.C., Duh, J.-D., 2000. Modeling the relationships between land-use and land-cover on private lands in the Upper Midwest, USA. Journal of Environmental Management 59, 247–263.

Brown, D.G., Page, S.E., Riolo, R.L., Rand, W., 2004. Agent based and analytical modeling to evaluate the effectiveness of greenbelts. Environmental Modelling and Software 19 (12), 1097–1109.

Brown, D.G., Johnson, K.M., Loveland, T.R., Theobald, D.M., 2005a. Rural land use change in the conterminous US, 1950–2000. Ecological Applications 15 (6), 1851–1863.

Brown, D.G., Page, S.E., Riolo, R., Zellner, M., Rand, W., 2005b. Path dependence and the validation of agent-based spatial models of land use. International Journal of Geographical Information Science 19 (2), 153–174.

Brown, D.G., Riolo, R.L., Robinson, D., North, M., Rand, W., 2005c. Spatial process and data models: Toward integration of agent-based models and GIS. Journal of Geographical Systems 7 (1), 1–23.

Chiang, A.C., 1984. Fundamental Methods of Mathematical Economics. Mcgraw-Hill, New York, pp. 788.

Daniel, T.C., 2001. Whither scenic beauty? Visual landscape quality assessment in the 21th century. Landscape and Urban Planning 54 (1–4), 267–281.

Deadman, P.J., Robinson, D.T., Moran, E., Brondizio, E., 2004. Effects of colonist household structure on land use change in the Amazon Rainforest: an agent based simulation approach. Environment and Planning B: Planning and Design 31, 693–709.

Evans, T.P., Sun, W., Kelley, H., 2006. Spatially explicit experiments for the exploration of land use decision-making dynamics. International Journal of Geographical Information Science 20 (9), 1013–1037.

Fernandez, L., Brown, D.G., Marans, R., Nassauer, J., 2005. Characterizing location preferences in an exurban population: implications for agent based modeling. Environment and Planning B 32 (6), 799–820.

US FHWA, 1989. FHWA Functional Classification Guidelines. US Federal Highway Administration, Washington, DC <http://www.fhwa.dot.gov/planning/fcsec1_1.htm>.

Forman, R.T.T., Sperling, D., Bissonette, J.A., Clevenger, A.P., Cutshall, C.D., Dale, V.H., Fahrig, L., France, R., Goldman, C.R., Heanue, K., Jones, J.A., Swanson, F.J., Turrentine, T., Winter, T.C., 2003. Road Ecology: Science and Solutions. Island Press, Washington, DC.

Geoghegan, J., Wainger, L.A., Bockstael, N.E., 1997. Spatial landscape indices in a hedonic framework: an ecological economics analysis using GIS. Ecological Economics 23 (3–5), 251–264.

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W.M., Railsback, S.F., Thulke, H., Weiner, J., Wiegand, T., DeAngelis, D.L., 2006. Pattern-oriented modeling of agent-based complex systems: Lessons from Ecology. Science 310 (5750), 987–991.

Groffman, P.M., Bain, D.J., Band, L.E., Belt, K.T., Brush, G.S., Grove, J.M., Pouyat, R.V., Yesilonis, I.C., Zipperer, W.C., 2003. Down by the riverside: urban riparian ecology. Frontiers in Ecology and Environment 1 (6), 315–321.

Hansen, A.J., Knight, R., Marzluff, J., Powell, S., Brown, K., Hernandez, P., Jones, K., 2005. Effects of exurban development on biodiversity: patterns, mechanisms, research needs. Ecological Applications 15 (6), 1893–1905.

Holland, J.H., 1995. Hidden Order: How Adaptation Builds Complexity. Massachusetts, Perseus Books, Cambridge.

Irwin, E.G., Bockstael, N.E., 2004. Land use externalities, growth management policies, and urban sprawl. Regional Science and Urban Economics 34 (6), 705–725.

Janssen, M.A., Ostrom, E., 2007. Empirically based agent-based modelling. Ecology and Society 11 (2), 37.

Lempert, R., Popper, S., Bankes, S., 2002. Confronting surprise. Source Social Science Computer Review 20 (4), 420–440.

Manson, S.M., 2001. Simplifying complexity: a review of complexity theory. Geoforum 32, 405–414.

Manson, S.M., O'Sullivan, D., 2006. Complexity theory in the study of space and place. Environment and Planning A 38, 677–692.

Marans, R.W., 2003. Understanding environmental quality through quality of life studies: the 2001 DAS and its use of subjective and objective indicators. Landscape and Urban Planning 65 (1–2), 75–85.

McGarigal, K., Marks, B.J., 1995. FRAGSTATS: Spatial Pattern Analysis Program for Quantifying Landscape Structure. General Technical Report PNW-GTR-351, USDA Forest Service, Pacific Northwest Research Station, Portland, OR.

Nassauer, J., 1995. Culture and changing landscape structure. Landscape Ecology 10 (4), 229–237.

Nassauer, J., Dayrell, E., Wang, Z. in preparation. What will the neighbors think? Cultural norms for ecological design.

O'Sullivan, D., 2004. Complexity science and human geography. Transactions of the Institute of British Geographers, NS 29, 282–295.

Page, S.E., 2005. Agent-based models. In: Newman, P., Eatwell, J., Millgate, M. (Eds.), The New Palgrave Dictionary of Economics. Palgrave MacMillan, New York.

Parker, D., Meretsky, V., 2004. Measuring pattern outcomes in an agent-based model of edge-effect externalities using spatial metrics. Agricultural Ecosystems and Environment 101 (2–3), 233–250.

Parker, D.C., Manson, S.M., Janssen, M.A., Hoffmann, M.J., Deadman, P., 2003. Multi-agent systems for the simulation of land-use and land-cover change: a review. Annals of the Association of American Geographers 93, 314–337.

Pickett, S.T.A., Cadenasso, M.L., Grove, J.M., Nilon, C.H., Pouyat, R.V., Zipperer, W.C., Costanza, R., 2001. Urban ecological systems: Linking terrestrial ecological, physical, and socioeconomic components of metropolitan areas. Annual Review of Ecology and Systematics 32, 127–157.

Polhill, J.G., Gotts, N.M., Law, A.N.R., 2001. Imitative versus non-imitative strategies in a land use simulation. Cybernetics and Systems 32 (1–2), 285–307.

Rand, W., Zellner, M., Page, S.E., Riolo, R., Brown, D.G., Fernandez, L.E., 2002. The complex interaction of agents and environments: an example in urban sprawl. In: Macal, C., Sallach, D. (Eds.), Proceedings, Agent 2002: Social Agents: Ecology, Exchange, and Evolution. Argonne National Laboratory, Chicago, IL, pp. 149–161.

Rand, W., Brown, D.G., Page, S.E., Riolo, R., Fernandez, L.E., Zellner, M. 2003. Statistical validation of spatial patterns in agent-based models. In: Proceedings, Agent Based Simulation, Montpellier, France, April 2003.

Robinson, D.T., Brown, D.G., Parker, D.C., Schreinemachers, P., Janssen, M.A., Huigen, M., Wittmer, H., Gotts, N., Promburom, P., Irwin, E., Berger, T., Gatzweiler, F., Barnaud, C., 2007. Comparison of empirical methods for building agent-based models in land use science. Journal of Land Use Science, in press.

Land Atlas and Plat Books., 1956–1999. Rockford Map Publishers, Inc., Rockford, IL, USA.

US Bureau of the Census, 2001. Census of Population and Housing: Summary File 1 United States. Bureau of the Census, US Washington, DC.

US Department of Agriculture, 2002. Census of Agriculture, Geographic Area Series. In: CD Cen V1 (6-04). USDA, vol. 1. National Agricultural Statistics Service, Washington, DC.

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

Wegener, M., 2005. Urban land-use transportation models. In: Maguire, D.J., Batty, M., Goodchild, M.F. (Eds.), GIS, Spatial Analysis, and Modeling. ESRI Press, Redlands, CA, pp. 203–220.

Zellner, M.L., Page, S.E., Rand, W., Brown, D.G., Robinson, D., Nassauer, J., Low, B., in review. The emergence of zoning policy games in exurban jurisdictions. Land Use Policy.