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Research Paper

Modeling landowner interactions and development patterns at the urban fringe

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ABSTRACT

Population growth and unrestricted development policies are driving low-density urbanization and fragmentation of peri-urban landscapes across North America. While private individuals own most undeveloped land, little is known about how their decision-making processes shape landscape-scale patterns of urbanization over time. We introduce a hybrid agent-based modeling (ABM) – cellular automata (CA) modeling approach, developed for analyzing dynamic feedbacks between landowners' decisions to sell their land for development, and resulting patterns of landscape fragmentation. Our modeling approach builds on existing conceptual frameworks in land systems modeling by integrating an ABM into an established grid-based land-change model – FUTURES. The decision-making process within the ABM involves landowner agents whose decision to sell their land to developers is a function of heterogeneous preferences and peer-influences (i.e., spatial neighborhood relationships). Simulating landowners' decision to sell allows an operational link between the ABM and the CA module. To test our hybrid ABM-CA approach, we used empirical data for a rapidly growing region in North Carolina for parameterization. We conducted a sensitivity analysis focusing on the two most relevant parameters—spatial actor distribution and peer-influence intensity—and evaluated the dynamic behavior of the model simulations. The simulation results indicate different peer-influence intensities lead to variable landscape fragmentation patterns, suggesting patterns of spatial interaction among landowners indirectly affect landscape-scale patterns of urbanization and the fragmentation of undeveloped forest and farmland.

1. Introduction

In many metropolitan regions, population growth and the demand for new development are transforming the form and function of landscapes. With a projected increase of global urban population from 2.6 billion in 2000 to 5 billion in 2030, this trend is likely to continue (United Nations & Department of Economic and Social Affairs (Population Division), 2015). Land-change models are valuable tools to simulate and explore spatiotemporal urbanization patterns and the effects of urbanization on landscapes surrounding urban centers (National Research Council, 2014; Rounsevell et al., 2012; Verburg, Kok, Pontius, & Veldkamp, 2006). Due to their ability to represent environmental heterogeneity, land-change models, particularly those based on cellular automata (CA), are frequently used for projecting urban growth (Herold, Goldstein, & Clarke, 2003; Koch, Wimmer, & Schaldach, 2018; White & Engelen, 1993). CA models simulate new development in locations of high suitability, based on a weighted overlay of locally important site suitability factors (Verburg et al., 2006). Areas identified as highly suitable for new development through CA are derived from empirical analyses of observed growth patterns.

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For example, the most suitable locations may be found adjacent to existing amenities such as roads and urban centers (Barredo, Kasanko, McCormick, & Lavalle, 2003; Koch, 2010; Meentemeyer et al., 2013). However, development does not always occur where expected due to stochastic processes and path dependencies (Brown, Page, Riolo, Zellner, & Rand, 2007).

Variability in development location is induced by human decision-making, where heterogeneities in personal preferences and priorities lead to differences in the locations of land-use activities (Janssen & Ostrom, 2006; Meyfroidt, 2013; Smith et al., 2017). Furthermore, the decision-making processes of landowners along the urban fringe, including those decisions resulting in urban sprawl, are notoriously difficult to unravel and represent within land-change models (Brown et al., 2008; Filatova, Parker, & Van Der Veen, 2009). Agent-based models (ABM) offer a way to incorporate human decisions in land-change models and improve representations of variability in land-change processes (Huang, Parker, Filatova, & Sun, 2014). Additionally, ABMs are ideal for modeling complex systems and patterns that emerge as a result of interactions between humans and their environments (An, 2012; Parker, Manson, Janssen, Hoffmann, & Deadman, 2003). To date, ABMs of land-change processes have primarily focused on studying urban settings using microeconomic assumptions of utility maximization (Groeneveld et al., 2017). The majority of these studies consider housing markets and residential choice from a buyer or developer's perspective (e.g., individual preferences for finding a location to build), often considering land prices as an important component of decision making (e.g., Filatova et al., 2009; Ligmann-Zielinska, 2009; Magliocca, Safirova, McConnell, & Walls, 2011). These models have demonstrated the influence of heterogeneous agents on model outcomes (Filatova, Voinov, & van der Veen, 2011; Magliocca, McConnell, Walls, & Safirova, 2012b), including effects on urban sprawl (Brown & Robinson, 2006; Magliocca, McConnell, & Walls, 2015).

In many growing regions of the U.S., development in the peri-urban area is driven by the desire for low-density housing and therefore takes on a distinct leapfrog pattern, where new development is discontinuous from existing urban areas (Irwin, Jayaprakash, & Munroe, 2009). Several causes leading to the process of leapfrogging have been explored, such as landowners who do not wish to sell undeveloped properties (Barnard & Butcher, 1989; BenDor, Shoemaker, Thill, Dorning, & Meentemeyer, 2014; Pyle, 1989). Individual decisions regarding land ownership and management may not only be driven by economic utility, but also nonmonetary values (Kauneckis & York, 2009; Mullendore, Ulrich-Schad, & Prokopy, 2015). For example, social factors like age, income, educational attainment, legacies, and lifestyles further influence landowners' willingness to sell their properties to developers (Jager, Janssen, De Vries, De Greef, & Vlek, 2000; Levine, Chan, & Satterfield, 2015; Robinson et al., 2007). Hence, understanding of land change processes could be improved by including high-quality data related to land-change agents, including various preferences, beliefs, and behaviors (National Research Council, 2014).

Landowners' preferences, beliefs, and behaviors are highly influenced by the preferences, beliefs, and behaviors of their peers (Huff, Leahy, Hiebeler, Weiskittel, & Noblet, 2015). Social norms, social interactions, knowledge transfer, and anticipating as well as learning strategies all influence individuals' decisions and affect how they manage their land (Chen, Vina, Shortridge, An, & Liu, 2014; Little & McDonald, 2007; Schlüter et al., 2017). Though peer-influence is not necessarily defined by geographic space, immediate neighbors can have a particularly strong effect on decisions when it comes to land management (Manson, Jordan, Nelson, & Brummel, 2016; Nassauer, Wang, & Dayrell, 2009). For example, a landowner may decide to sell their land after learning that a neighbor is selling their land, or lobby neighbors not to sell to conserve neighborhood character. Agent-based modeling approaches have been developed to study landowners' decision making processes; Huff et al. (2015) implemented a simulation model that includes neighborhood interactions as part of land-management decisions and Magliocca et al. (2011) developed a model to test the importance of economic values and amenities on development. While this previous research has advanced our understanding of the role social networks and economic values play in spatial development patterns, there is a need for modeling frameworks capable of exploring social values (in addition to economic) and their interplay with other traditional drivers of development in peri-urban areas (Groeneveld et al., 2017). Including peer-influence and heterogeneous values in ABMs of landowners' decisions can improve our understanding of the processes that generate urbanization patterns and aid urban planners in preparing for future development.

The objective of this paper is to introduce a hybrid ABM-CA model, designed for analyzing how the relationships between peer-influence and heterogeneous values influence spatiotemporal patterns of development in peri-urban areas. In the following, when using the term peer-influence, we refer to the relationship between a focal agent and the agents in its direct spatial neighborhood. To avoid being repetitive by building "yet another model" (O'Sullivan et al., 2015), we build on existing modeling frameworks and combine them in an ABM-CA model called FUTURES-ABM. We use the established FUTURES model (Meentemeyer et al., 2013) as the CA component. The FUTURES framework is unique in that it combines a field-based with an object-based representation of land change, geared at providing a tool for analyzing the spatial structure of development of peri-urban landscapes. It was validated for the metropolitan region of Charlotte, North Carolina (Meentemeyer et al., 2013), and has been successfully applied in a set of case studies located in North Carolina (Dorning, Koch, Shoemaker, & Meentemeyer, 2015; Petrasova et al., 2016; Pickard, van Berkel, Petrasova, & Meentemeyer, 2017). This CA component enables the representation of environmental factors, their spatial heterogeneity, and their effect on development patterns. We enhance the CA model with an ABM component, based on conceptual frameworks in the ABM literature (Valbuena, Verburg, Bregt, & Ligtenberg, 2010). The ABM component is customized to focus on social processes underlying landowners' decisions that shape variability in patterns of development (Delre, Jager, Bijmolt, & Janssen, 2010; Janssen, 2011).

The resulting hybrid FUTURES-ABM framework allows exploring new questions related to how heterogeneous values and peer-influence shape landscape-scale patterns of urbanization. We use a sensitivity analysis, embedded in a simulation experiment, to demonstrate how the inclusion of these social and environmental factors can influence the simulation results. The sensitivity analysis focuses on the components which we consider innovative contributions to the field of hybrid ABM-CA models for the analysis of peri-urban areas. These components are (1) a diverse actor typology including developer and landowner agents, (2) a spatial neighborhood process affecting actors' decision making, and (3) an additional level of decision making—the parcel level.

2. Methods

2.1. Model description

We designed FUTURES-ABM for exploring the decision-making process of heterogeneous landowners, and for analyzing how these decisions contribute to emergent landscape patterns in peri-urban areas. By combining the utility of a CA urban growth model with a process-based ABM, we can simulate the complex spatial interactions between urban developers, landowners targeted for the purchase of land, and the environment. We also incorporate agents' peer (neighborhood) networks to evaluate how peer-influences affect landscape-scale patterns of urbanization. First, we give an overview of the FUTURES-ABM modeling framework. We provide further documentation of the framework's systematic details, based on the ODD protocol (Grimm et al., 2010), in the Supplementary Material in Appendix A. The ODD protocol also includes a description of input data used to parameterize the model and to drive scenario simulations (see Section A3.2 Input Data).

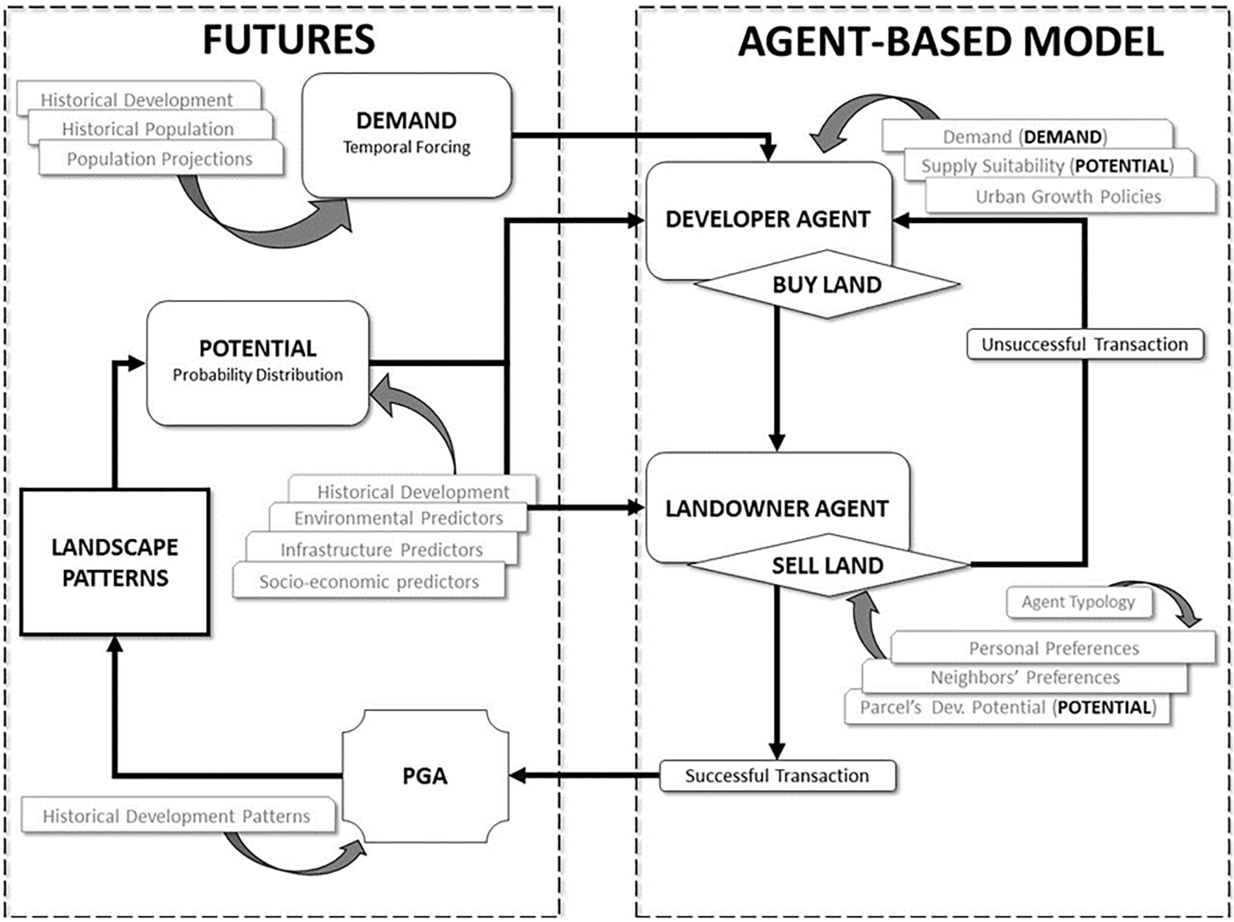


Fig. 1. Schematic view of the FUTURES-ABM modeling framework. FUTURES-ABM consists of three sub-modules (POTENTIAL, DEMAND, and patch-growing algorithm (PGA)), and includes two interacting agent types: A developer collective agent and a heterogeneous set of landowner agents. A developer agent decides to buy land based on market demand for development and the suitability of the target parcel. Landowner agents will sell property to the developer agent based on their internal willingness to sell and the willingness of their neighbors to sell. If a landowner agent decides to sell, the transaction is successful and a development is built using the PGA. If they do not sell, the transaction is unsuccessful and the developer moves on to the next suitable property. Landscape patterns and agent characteristics are updated at each simulation step.

FUTURES-ABM consists of three sub-modules (POTENTIAL, DEMAND, and the patch-growing algorithm (PGA); see Fig. 1), and includes two interacting agent types: a developer collective agent and a heterogeneous set of landowner agents. The landowner agent types can be characterized by different levels of attachment to their land and profit-seeking motivations (see Section 2.2.3). Landowner agents make the decision to sell or not to sell undeveloped parcels of land. In the model, this decision-making process is influenced by the individual landowner agent's characteristics, personal land ownership values or attachments, and the average site suitability (POTENTIAL sub-module) of their parcel. The agent's decision making can also be influenced by the intentions of their neighbors to sell their properties.

Demand for urban development is prescribed based on projections of historical population and urban growth (DEMAND sub-module). When demand for urban development exists, the developer agent selects a parcel of land for development based on site suitability, evaluating environmental characteristics associated with historical urban growth (POTENTIAL). After a parcel is selected, the developer approaches the corresponding landowner agent and offers to buy their land. The landowner agent is activated to make a decision about whether or not to sell the parcel to the developer. Upon a successful developer-landowner transaction, the PGA sub-module creates a patch of newly developed land as described by the FUTURES framework (Meentemeyer et al., 2013). If the transaction fails (i.e., the landowner agent is not willing to sell), the developer agent moves on to another location and, hence, another landowner agent. This process continues until the demand for development is met for each specified time interval. In the case that no landowner agents are willing to sell their land to meet the demand for development, the simulation stops.

In summary, urban land-use transitions only occur when there is demand for developed land and suitable undeveloped parcels are available where a landowner agent is willing to sell that property to a developer. Demand and suitability are, among other factors, controlled by market forces, while landowner willingness to sell is related to individual factors, such as attachment to the land and knowledge of neighbors' willingness to sell their own properties. For details on the model implementation of willingness to sell, see the ODD protocol (Appendix A).

2.2. Simulation experiment

2.2.1. Overview

We conducted a simulation experiment in order to test the functionalities of the FUTURES-ABM modeling framework and to understand how the newly implemented processes manifest themselves at the landscape level. A description of the key functionalities and processes of FUTURES-ABM is included in the ODD protocol (Appendix A). As a test case, we selected the rapidly urbanizing area Cabarrus County, North Carolina, using existing empirical data for measuring urban growth. Here, we describe parameterization details of the model and present a simulation experiment that illustrates key features of FUTURES-ABM.

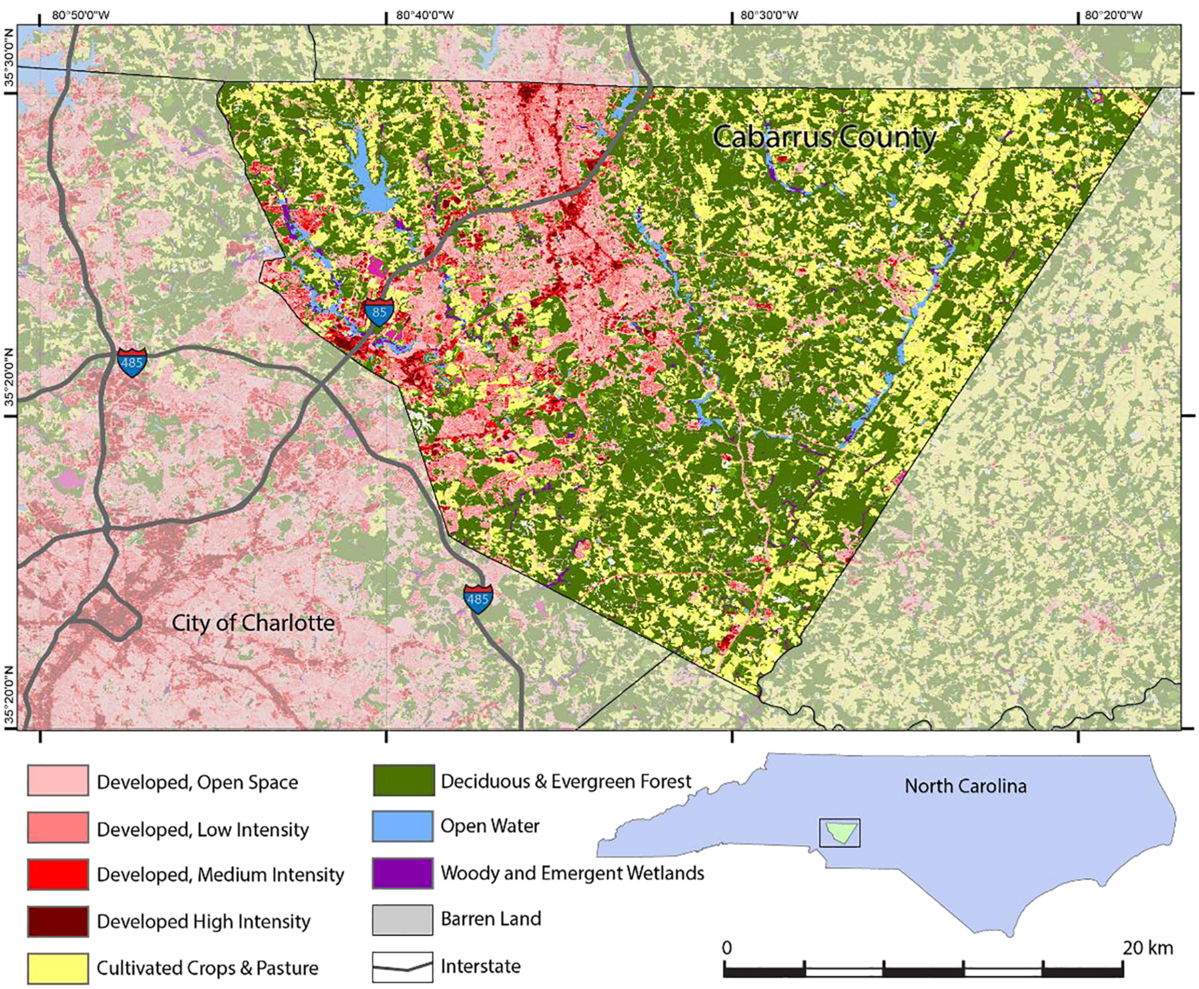


Fig. 2. Location of Cabarrus County land use (2011, NLCD) and proximity to the city of Charlotte.

2.2.2. Study area

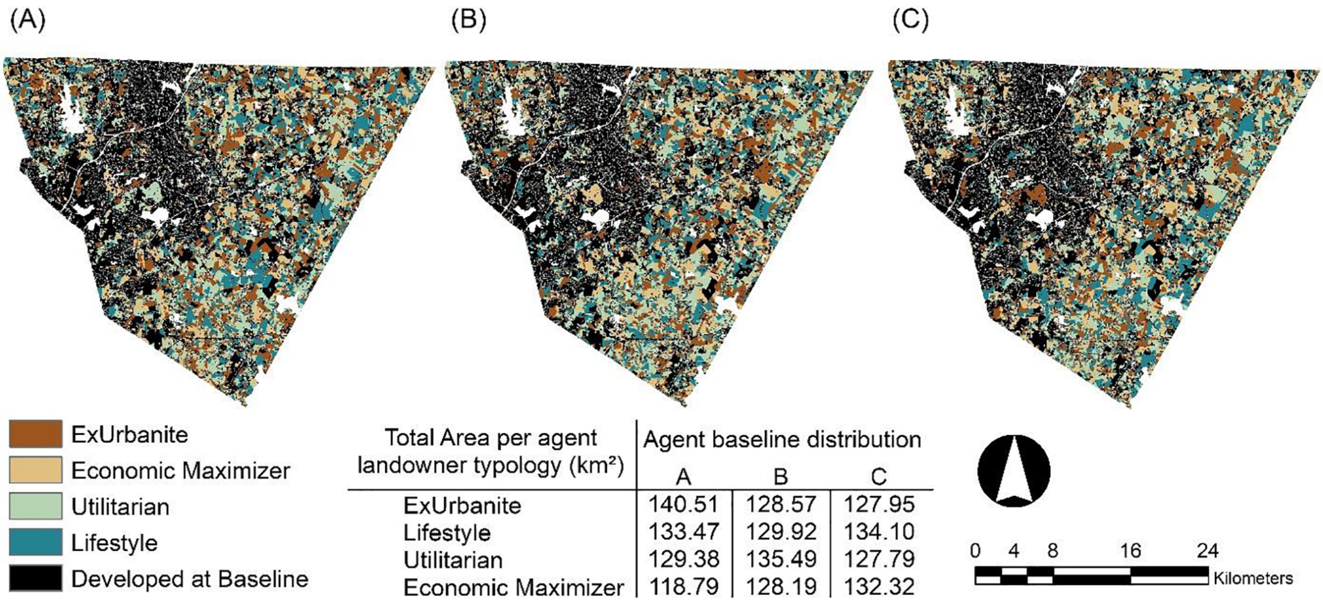
Cabarrus County is part of the Charlotte-Concord-Gastonia Metropolitan Statistical Area (Fig. 2), which is ranked as one of the fastest growing urban areas in the United States (United States Census Bureau, 2017). In 2006, the base year of our simulation experiment, 114,989 people lived in Cabarrus County. Over the last four decades, the county has experienced a significant increase in population from 75,026 in 1970 to 194,652 in 2016. Of the county's total 94,404 ha, approximately 42.8% (40,440 ha) is urban, 15.4% (14,573 ha) is categorized farmland, 32.8% (30,994 ha) is forest, and 9.0% is other natural vegetation. We used a parcel dataset from Census.gov to define the boundaries of landownership for agents. In 2014, Cabarrus County had 110,406 parcels, of which 29,790 were located on undeveloped land in 2006 and, hence, candidates for development during simulation runs. Of these 29,790 parcels, not all were owned by individual landowners, but some landowners own more than one parcel. According to the raw parcel data, there are 16,820 individual landowner agents that own developable land.

Suburban development in the region is primarily driven by urban spillover from the nearby city of Charlotte. Patterns of new development in Cabarrus County are influenced by environmental factors like transportation infrastructure, the production potential of working lands, and proximity to Charlotte's urban center (Meentemeyer et al., 2013). Although Charlotte has encouraged revitalization and densification through the expansion of urban amenities and development plans designed to accommodate its rapid growth, construction of Interstate 485 (Fig. 2) has opened up vast amounts of land for sprawling suburban development (Delmelle, Zhou, & Thill, 2014).

2.2.3. Experimental design

In this experiment, we focused on three components that we consider innovative contributions to the field of ABM-CA hybrid modeling and simulation of spatial development patterns: (1) extension of agent types typically included in ABM models of urban development (i.e., going beyond the developer agent and including different agent types representing a typically understudied decision maker in the peri-urban area – the landowner); (2) inclusion of an additional spatially explicit decision-making process (i.e., the consideration of neighbors' peer-influence on landowners' decision to sell or not sell their land to developers); and (3) consideration of an additional spatial level of decision making on land change (i.e., the combination of the grid-based CA and the parcel-based ABM). To test the effect of the first two characteristics on development patterns, we varied two main model parameters in our simulation experiment: the initial distribution of landowner agents in the landscape and the intensity of peer-influence on landowner decisions to (not) sell their land to the developer agent. Overall, our simulation experiment evaluates 15 different parameterizations by varying these critical parameters.

We assessed the sensitivity of the FUTURES-ABM to landowner agent locations by generating three different random realizations of distributing these agents in the landscape (Fig. 3). While agent age and income were held constant and allocated based on representative disaggregation of census data (see Appendix A), no information on the specific location of different agent types is available. We approached this lack of information by including the location of agents of different types (ExUrbanite, Lifestyle, Utilitarian, Economic Maximizer) as a factor in the sensitivity analysis. Each of the three agent distributions



Total Area per agent landowner typology (km²)	Agent baseline distribution A	B	C
ExUrbanite	140.51	128.57	127.95
Lifestyle	133.47	129.92	134.10
Utilitarian	129.38	135.49	127.79
Economic Maximizer	118.79	128.19	132.32

Fig. 3. Three different initial distributions of landowner agents in the landscape (A, B, and C). Agent age and income are held constant, while the landowner agent type is randomly assigned to parcels.

used the same percentage of landowner agents per type (25% each); however, they differed in their parcel allocations. In other words, an agent type was randomly placed on one parcel resulting in three differing landscape realizations for each of the simulation experiments. We intentionally chose an even distribution of agents across parcels (one fourth of the developable parcels for each of the four agent types) in order to allow for an easy interpretation of the effect of agents' varying positions in the landscape on the simulated urbanization patterns. However, it is important to emphasize that the agent allocation is based on percentage of parcels and not percentage of landscape, leading to slightly different values of total area owned by agent type (Fig. 3) for the three different distributions. This experimental design was loosely based on two studies in the field of urban simulation modeling, those of White and Engelen (1993) and Brown et al. (2007), which also test the effect of varying landscape initializations on simulation results.

We tested the effect of peer-influence on urbanization patterns by modifying the influence that landowner agents' peers have on their willingness to sell (WTS). Willingness to sell values range from 0 to 1, with 0 indicating no willingness and 1 showing complete willingness to sell a parcel to the developer agent collective. Initial probabilities of individual willingness to sell (WTS_I) based on age, income, landowner agent type, and parcel desirability (see Section 2.2.4) were modified based on average neighboring willingness to sell (WTS_P), according to Eq. (1).

$$Willingness\ To\ Sell = (WTS_P * PW) + (WTS_I * (1 - PW)) \quad (1)$$

We varied the degree of peer-influence (PW) from 0 to 1 with five levels: **ZERO (0), LOW (0.25), MEDIUM (0.5), HIGH (0.75), and TOTAL (1.0)**, in order to test the sensitivity of the simulation model to this parameter.

We combined each of the three landowner agent randomizations with each level of peer-influence while holding all other model parameters constant. Since FUTURES-ABM includes non-deterministic components, we carried out 10 simulation runs for each parameterization resulting in a total of 150 simulations. We ran simulations for 20 steps corresponding to a time period of 20 years. While 10 simulation runs is modest in comparison to similar agent-based modeling experiments, the large number of agents in our simulation (N = 16,820) made for prohibitive extended runtimes. We provide a detailed description of the numerical values used for the simulation experiment in Section 2.2.4 and Appendix A, Section A3.

We calculated five different landscape class metrics using FRAGSTATS (McGarigal, 2015). While these metrics do not affect actors' decision making, they provide a way to analyze the effect of landowner agents and different parameterizations on the size and spatial configuration of newly developed urban areas. The calculated class metrics included the percentage of the landscape occupied by urban area (PLAND), the number of urban patches (NP), the largest patch index providing the percentage of the landscape occupied by the largest urban patch (LPI), the total edge length of urban patches (TE), and the clumpiness index (CLUMPY). Values for the clumpiness index range from −1 to 1, with -1 indicating maximum disaggregation of urban patches and 1 indicating maximum aggregation of urban patches. A detailed description of the five class metrics can be found in McGarigal (2015).

2.2.4. Model parameterization

2.2.4.1. DEMAND sub-module. Demand for new urban developments is based on state population projections and expected land consumption (e.g., people per impervious land unit area). For this purpose, we extrapolated the relationship between impervious surface and population numbers based on observations for the period 1976–2006 for the "status quo" scenario used for all simulations in this study. In Cabarrus County, population per impervious area has decreased over the last decades from 11.39 people/hectare in 1992 to 7.84 people/hectare in 2011. Under the "status quo" scenario, the trend of decreased population density continues. Given this rising land consumption and state projections predicting an increase of approximately 50,000 people over the next 20 years, we assumed growing demand for urbanization. More details on the specification of the "status quo" are provided in Dorning et al. (2015).

2.2.4.2. POTENTIAL sub-module. In the study region, distance to overpasses and transportation networks are foci of urban expansion. Adjacency to existing urban areas and the central business district attract developments, while topography shapes where urbanization occurs due to construction limitations of steeper slopes. We parametrized the POTENTIAL sub-module according to these qualities as described by the "status quo" specification in Dorning et al. (2015) for all model runs. The developer collective considers the potential when deciding which parcels to buy as well as other idiosyncrasies that might influence location choice.

2.2.4.3. PGA sub-module. The size and extent of an individual new development patch was prescribed by historical growth where developers randomly draw from a calibrated pool of patch sizes and grow or develop cells based on land suitability described by Meentemeyer et al. (2013).

2.2.4.4. Developer collective. In the model, the developer collective utilizes information provided by FUTURES sub-modules (DEMAND, POTENTIAL, PGA) to develop land. Developers respond to new demands for housing, infrastructure, and associated commercial and industrial buildings by searching for suitable locations for land development and choosing locations based on site suitability. Developers approach landowners of the selected, suitable locations and ask if they are willing to sell their land before determining if they will buy a parcel and commence construction. If the landowner is willing to sell, the developer builds a new patch of development according to PGA specifications.

2.2.4.5. Landowner agents. We characterized landowners based on a survey of woodland owners in Cabarrus and adjoining counties in the Charlotte metropolitan region, which was part of a study on urban woodland owners conducted by BenDor et al. (2014). Even though landowners are not limited to woodland owners in the model, the survey was the only available dataset suitable to parameterize landowner agents. In the survey, respondents' attachment to their land and land management goals were investigated and related to socioeconomic and spatial determinants that might explain these perspectives (BenDor et al., 2014). Estimates of landowners' willingness to sell were determined using a logistic regression model where the intention to, the current listing of, or economic motivation for selling their property was used as the dependent variable. Predictor variables include the landowner's age and income level, the mean development potential of their property (POTENTIAL sub-module), and their agent type (Table 1). Our general model indicates that with increasing age and income, woodland owners are more likely to sell their land. They also respond to site suitability of their land, likely anticipating and deciding to sell their lands based on incoming development. Despite moderately well fit (AUC = 0.76) model estimates of the probability for willingness to sell, we believe our parameterization is the best available representation of landowner behavior in this region.

We developed the landowner agent typology (Table 1) based on a cluster analysis of the surveyed private urban woodland owners, grouping like values based on multiple forest value responses (BenDor et al., 2014). We parameterized owner types given a spectrum of land attachment and lifestyle parameters, which we assumed influences their willingness to sell due to different utilities. We included (1) an ExUrbanite agent that due to their high to moderate attachment to their woodlands are less likely to want to sell their property; (2) a Lifestyle agent highly attached to their woodland, willing to sell their land given changes to the character of the surrounding landscape; and (3) a Utilitarian agent that while valuing the productive capacity of their woodlands would also sell their land if it were financially beneficial. In addition, since this survey was based on private owners of undeveloped land, we lacked a landowner type that was representative of a motivated seller. We therefore added (4) an Economic Maximizer agent type to represent those landowners whose primary motivation is to sell property, such as corporations or absentee owners. While we realized these typologies may not encompass the full range of landowner types owning undeveloped land in the region, this application demonstrates the utility of integrating survey data in the ABM-CA framework. A representative survey of owners of undeveloped land in the area of interest would include canvassing these motivated owners.

Table 1
Parameterization of individual landowner agent type's willingness to sell their property (WTS_I). Utility function of each type is calculated as follows: (AGE × 0.0032) + (POTENTIAL × 0.869) + (INCOME * 0.00000486) + (ExUrbanite × −19.8) + (Lifestyle × −3.8) + (Utilitarian × −2.1) + (Economic Maximizer × 1), where each agent type is represented by 0 or 1, indicating the type of agent under consideration. We apply Logit transformation to individual utility to determine the probability of an agent selling their property.

Agent Type	Description	WTS_I
ExUrbanite	Conservative actors with conservative woodland values (not in the political sense).	–
Lifestyle	Highly value woodlands.	–
Utilitarian	Value services provided by woodlands.	−/+
Economic Maximizer	Primary motivation is to sell property, e.g. corporations or absentee landowners.	+ +

3. Results

3.1. Completion of simulation runs

Of the 30 simulation runs for understanding the effect of landowner agent distribution in the landscape (i.e., the three different initial distributions of landowners in the landscape with ZERO peer-influence, each repeated 10 times), 20 did not fully execute to the intended 20 simulation steps (Table 2 – see "ZERO peer-influence" column). The number of completed simulations differed between the three initial distributions of landowners in the landscape. Further analysis of the simulation results indicated that incomplete runs were due to a lack of landowner agents willing to sell their land, cumulatively resulting in relatively low average landscape-level decision to sell. The average area comprising owners choosing to sell ranged from 30% for landscape A to about 31% percent for landscape C, with landscape C having the highest number of completed simulation runs (Table 3 – see "ZERO peer-influence" column). This spatial variability in selling was also the result of highly suitable land for urban development being overlaid with different actor types, and hence willingness to sell values, caused by the initial distributions of landowners in the landscape.

Simulation runs including LOW, MEDIUM, HIGH, and TOTAL peer-influence levels showed that peer-influences also affected model completion with greater peer-influence resulting in fewer completed simulation runs (Table 2). Increased levels of peer-influence decreased the number of landowners deciding to sell across the landscape (Table 3), limiting the number of parcels available for the developer agent to buy. The 30 simulation runs for TOTAL peer-influence had the fewest completed simulation steps, ranging between six and nine despite numerous parcels potentially available for development. Related to the low number of completed simulation runs, peer-influence had a significant dampening effect on the landowners' WTS, with TOTAL peer-influence resulting in only 10% of the landscape with agents deciding to sell their property (Table 3).

3.2. Development locations

To control for non-completion across model runs, we analyzed the land-use/cover maps for each simulation run at simulation step six, the last step completed by all 150 simulation runs. We mapped the average number of occasions a parcel is developed across the 10 repetitions for each parameterization. The development probability maps for ZERO peer-influence and time step six indicated relatively little development

Table 2
Number of completed simulation steps for different peer-influence levels and the three initial distributions of landowner agents in the landscape (A, B, and C).

Scenarios	ZERO peer-influence			LOW peer-influence			MEDIUM peer-influence			HIGH peer-influence			TOTAL peer-influence		
Agent baseline distribution	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
Number of simulation steps successfully completed	18	18	19	19	20	20	18	19	20	11	11	12	6	6	7
	18	19	19	19	20	20	19	19	20	12	11	12	7	7	8
	19	19	19	20	20	20	19	20	20	12	12	12	7	7	8
	19	19	19	20	20	20	19	20	20	12	12	12	7	7	8
	19	19	20	20	20	20	19	20	20	12	12	12	7	7	8
	19	19	20	20	20	20	19	20	20	12	12	12	7	8	8
	19	19	20	20	20	20	19	20	20	12	12	14	7	8	8
	19	20	20	20	20	20	20	20	20	12	12	14	7	8	8
	19	20	20	20	20	20	20	20	20	12	12	19	8	8	9
	20	20	20	20	20	20	20	20	20	13	12	20	8	8	9

overall (16.7%–17.6% of the landscape), but a high level of agreement on the parcels selected for development (Fig. 4). Approximately 3.7% of the undeveloped land had a development probability of 90% or greater. These parcels were mainly located in close proximity to developed areas, the central business district of Concord (the county seat), and along transportation infrastructure (I-85 and NC Highway 49) in the central and north-central parts of Cabarrus County. This indicates that the developer agent, approaching landowner agents on parcels with high environmental suitability first, was successful in purchasing the corresponding parcels for development.

For the parameterizations with LOW, MEDIUM, and HIGH peer-influence, the location of development probability showed little variability (Fig. 5). Again, most of the new development was located near existing urban areas and along transportation infrastructure. Compared to the ZERO peer-influence scenario, the LOW, MEDIUM, and HIGH peer-influence scenarios resulted in more areas with medium development probability (i.e., there was less agreement between the 10 repetitions for a scenario-landscape combination). Only about 3.3%, 2.9%, and 2.4% of the parcels selected for development had a development probability of 90% or higher under the LOW, MEDIUM, and HIGH peer-influence parameterizations, respectively.

The mapped simulation results showed the importance of spatial interactions among agents on the locations of development probability and development patterns in general; differences in development locations were clearly noticeable for experiments with total reliance on peer-influence for willingness to sell values. The TOTAL peer-influence maps indicated a larger area of parcels identified for development with lower development probabilities on average. This is an indicator of the rejection of sale offers, which leads to an increasingly random allocation of developed cells resulting in a "fuzzy" development probability pattern. Only a low value of 2.6% of the parcels identified for development had a development probability of 90% or higher.

3.3. Development patterns

Spatial patterns of development showed minimal variation between the three different initial distributions of landowners in the landscape (Fig. 6). Overall, simulation results for the percentage of the landscape developed (PLAND) after simulation step six did not display significant differences for any of the 15 parameterizations. All of them showed around 47% of the landscape as developed. The class level metrics NP, LPI, TE, and CLUMPY also displayed little difference between the three distributions of landowners in the landscape (Fig. 7).

In contrast, the peer-influence level had a considerable effect on the resulting spatial development patterns. For the ZERO peer-influence scenarios, we found a qualitative difference in the number of patches and the percentage of the landscape occupied by the largest patch (Fig. 7). ZERO peer-influence (i.e., ignoring the spatial neighborhood's willingness to sell) resulted in a significantly higher number of patches and smaller largest patches. This finding was consistent across all landscape configurations. In combination with higher values for total edge lengths and lower values for clumpiness (Fig. 7), these results indicated higher landscape fragmentation for the ZERO peer-influence scenario results.

Percentage of landscape developed, number of patches, and largest patch index did not show a difference between the parameterization with LOW, MEDIUM, HIGH, and TOTAL peer-influence (Figs. 6 and 7). However, the total edge length was consistently higher, and the clumpiness index was consistently lower, for parameterizations with TOTAL and HIGH peer-influence as compared to those with MEDIUM and LOW peer-influence (Fig. 7). Lower total edge lengths and a higher clumpiness index indicated the least landscape fragmentation under these parameterizations.

3.4. Actor diversity

Development patterns and pattern metrics showed little variation between the simulation runs with LOW, MEDIUM, HIGH, and TOTAL peer-influence. There was, however, a qualitative difference between the simulation runs with peer-influence and the simulations with ZERO peer-influence. In the ZERO peer-influence parameterization, the different landowner agent types covered the range of willingness to sell values, leading to heterogeneous conversion rates (Table 4). Agents' willingness and decisions to sell varied greatly by agent type, with

Table 3
Landscape-level decision to sell at simulation step six for different peer-influence levels and the three initial distributions of landowner agents in the landscape (A, B, and C).

Scenario	ZERO peer-influence			LOW peer-influence			MEDIUM peer-influence			HIGH peer-influence			TOTAL peer-influence		
Agent baseline distribution	A	B	C	A	B	C	A	B	C	A	B	C	A	B	C
Average percent of landscape with positive decision to sell	29.6	30.0	30.9	24.8	24.8	25.4	19.1	19.3	20.9	14.5	14.6	15.3	9.6	9.4	10.4
Maximum	30.7	31.1	32.7	25.9	25.9	27.6	20.3	19.9	22.4	15.8	16.3	15.8	10.8	9.8	11.1
Minimum	29.6	28.7	29.7	24.0	24.0	24.5	18.1	17.7	20.2	13.5	13.7	14.2	8.2	9.0	9.4
Standard deviation	0.8	0.8	0.9	0.6	0.6	1.0	0.7	0.7	0.8	0.8	0.8	0.5	0.8	0.3	0.5

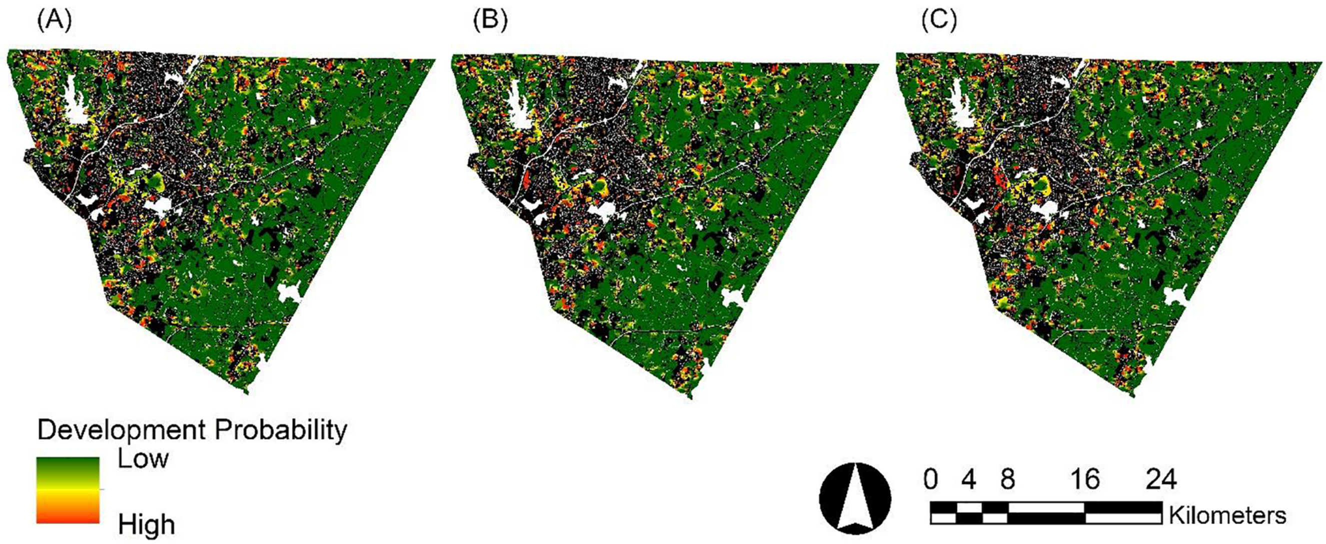


Fig. 4. Development probability maps for ZERO peer-influence and three different initial distributions of landowners in the landscape (A, B, and C). A high development probability value indicates areas where all 10 simulation runs indicate development; low development probability values indicate areas where the opposite is true.

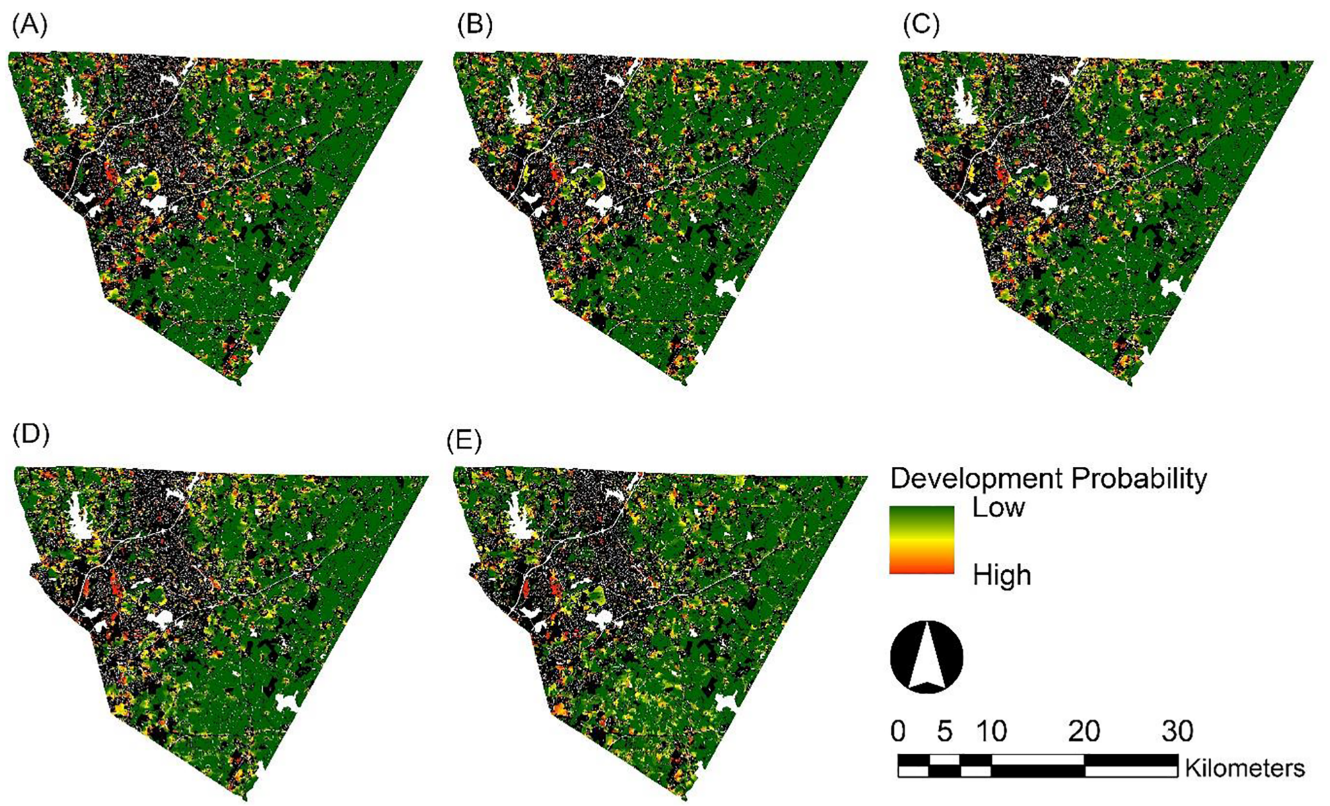


Fig. 5. Development probability maps for landscape configuration A and (A) ZERO peer-influence, (B) LOW peer-influence, (C) MEDIUM peer-influence, (D) HIGH peer-influence, (E) TOTAL peer-influence. A high development probability value indicates areas where all 10 simulation runs indicate development; low development probability values indicate areas where the opposite is true.

ExUrbanites and Lifestyle agents having lower WTS values and lower urban development conversion rates compared to Economic Maximizers and Utilitarian agents (Table 4). In the MEDIUM peer-influence parameterization, the same pattern was visible. Economic Maximizers sold 19,224 cells, while ExUrbanites, who were highly attached to their land, sold 9980 cells despite having equal numbers of each agent-type (Table 5). Comparing the results for ZERO and MEDIUM peer-influence parameterizations showed that mean values for decision to sell were lower for MEDIUM peer-influence for two out of four agent types (Tables 4 and 5). However, the mean willingness to sell was higher for ExUrbanites, Lifestyle, and Utilitarian agents under MEDIUM peer-influence. These results not only demonstrated the moderating influence of peer-influence on the agent's decision to sell (see also Tables 2 and 3), but also the importance of a heterogeneous agent typology for capturing a variety of values and attitudes. Variation in agent characteristics and the level of peer-influence resulted in different rates of sale for each group.

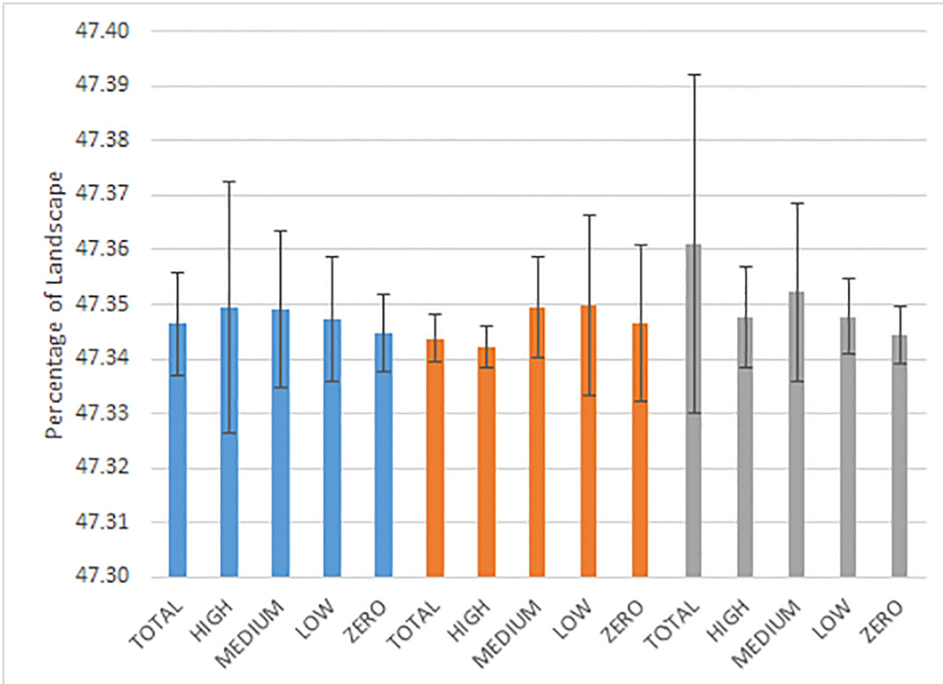


Fig. 6. Percentage of landscape developed (PLAND) after simulation step six, for landscape configuration A (blue), B (orange), and C (grey). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

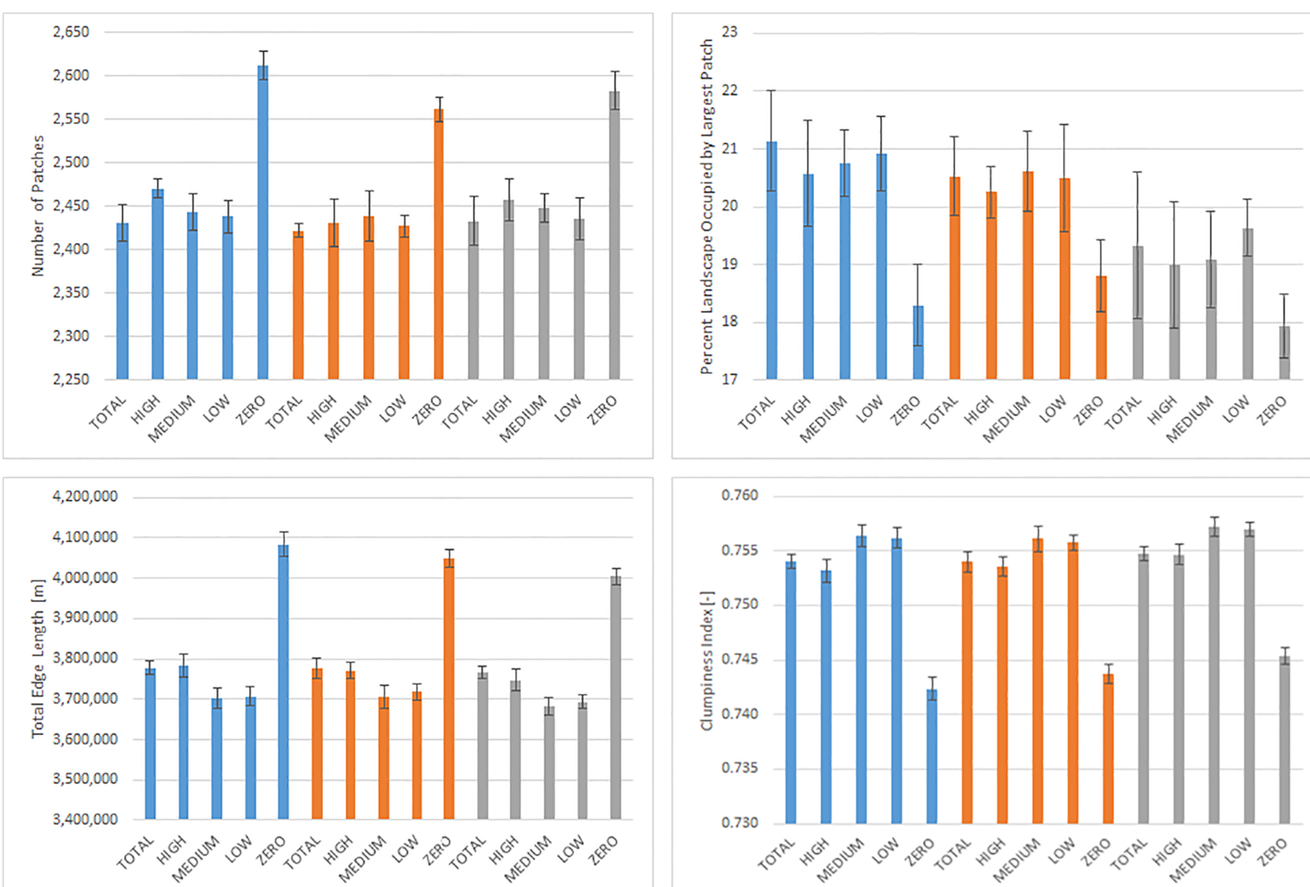


Fig. 7. Class-level metrics Number of Patches (NP), Total Edge Length (TE), Percentage of Landscape Occupied by Largest Patch (LPI), and Clumpiness Index (CLUMPY) for different levels of peer-influence and the three landscape configurations A (blue), B (orange), and C (grey). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Differences in conversions and selling characteristics for the landowner agent types under **ZERO** peer-influence intensity.

	Total Converted				Converted Rate				Willingness to Sell				Decision to Sell			
	Max	Min	Sd	Avg	Max	Min	Sd	Avg	Max	Min	Sd	Avg	Max	Min	Sd	Avg
ExUrbanite	3933	1498	611	2770	2.57%	1.02%	0.40%	1.83%	0.45	0.33	0.025	0.38	6.67%	2.71%	1.11%	4.47%
Lifestyle	8941	4255	1194	6463	4.68%	3.73%	0.28%	4.14%	0.46	0.35	0.036	0.40	8.32%	7.33%	0.24%	7.94%
Utilitarian	14,792	10,084	1216	12,521	9.90%	6.72%	0.80%	11.43%	0.52	0.45	0.019	0.48	13.97%	7.80%	1.50%	10.10%
Economic Maximizer	24,827	17,815	1792	21,424	18.68%	13.59%	1.39%	15.98%	0.65	0.37	0.063	0.56	30.05%	22.56%	1.68%	26.63%

4. Discussion

We introduced three main components in a hybrid ABM-CA modeling approach: a heterogeneous landowner (seller) agent typology; peer-influence based on spatial neighborhood; and the combination of a CA approach with the parcel level as the basis for decision-making. To avoid redundancy, we used existing modeling frameworks and concepts, combining the FUTURES model (Meentemeyer et al., 2013) with conceptual frameworks introduced by Valbuena et al. (2010) and Janssen (2011). We conducted a simulation experiment, including a sensitivity analysis, to demonstrate how the newly introduced model features can improve understanding of the complex spatial relationships between agents and landscapes, and how they shape development patterns in peri-urban areas. Our analysis demonstrates how the parameterization and distribution of agents and corresponding willingness to sell may influence model functionality and simulation outcomes. We also showed that varying degrees of peer-influence affected the contiguity of (simulated) urban development patterns.

4.1. New model components for land change studies

Many land-change models, especially when designed to operate on the regional to global scale, use a CA approach with the grid cell as the basic spatial unit of change. This approach has limited potential for implementing human decision-making regarding development, which typically does not happen at the grid level but at the parcel level due to ownership and land-management patterns (Brown, Pijanowski, & Duh, 2000). Hence, recent approaches focus on integrating the parcel level as the spatial unit of decision-making for land-change simulations (Sohl, Dornbierer, Wika, Sayler, & Quenzer, 2017). We expand on approaches for merging grid and parcel boundaries by combining the CA-based FUTURES (Meentemeyer et al., 2013) framework with parcel-level ownership information in the form of an ABM. This integrated approach is augmented by the theoretical foundation of the agent-based decision-making framework. We use the concepts introduced by Valbuena et al. (2010) and Janssen (2011) to study how preferences and values of parcel owners or managers may shape the development process in peri-urban areas.

The resulting hybrid FUTURES-ABM also expands on the typology of agents represented in agent-based studies of urbanization. Typically, ABMs only include agents who are motivated by utility (i.e., financial) maximization; this dismisses the effect of heterogeneous landowner preference and motivations on spatial patterns of development. For example, Filatova's (2015) ABM of an urban housing market focused on one type of seller agent owning already developed land and generated important findings on spatial pricing dynamics; however, the expansion of developed areas (or actual development of a parcel) was not modeled. Work by Magliocca, McConnell, Walls, and Safirova (2012a,b) also builds on microeconomic assumptions, including spatial patterns of urban expansion in ABM simulations for testing theoretical agent interaction and resulting landscape configurations. However, the underlying microeconomic assumptions of these models do not account for differences in individual utility and the influence of peers on the selling processes. We build on these studies by accounting for the social processes involved in land transactions including a heterogeneous agent typology allowing us to represent differences in agents' demographic values and the influence that neighbors (peer-influence) may have on their willingness to sell.

4.2. Influence of new model components

Our simulated land-use maps show qualitatively realistic development patterns. We attribute this to including both environmental and social drivers of land transitions that better represent the complex spatial interactions involved in land purchases at the urban fringe. Frameworks conceptualizing social processes as stochastic or using abstract homogenous behavioral theory oversimplify the important socio-spatial variations that influence spatial pattern (An, 2012). Inclusion of parcel boundaries as discrete decision units that can be partially or fully developed given agent and developer preferences also influenced the realism of simulation results. While non-urban parcels are often completely utilized in urban development, regulation for proportion of green space and complex tenure arrangement can result in both impervious and pervious land covers on the same parcel. By combining the patch-growing algorithm of the FUTURES model at the cellular level, and agents with discrete control over the sale of parcels (Fig. 1), we were able to simulate this variation in urban patches noticeable in landscape outcomes at the urban fringe.

While the high number of incomplete simulation runs was unintended and a surprising result, it informed our understanding of how heterogeneous agent types and their interactions with neighbors affect urban transitions. Increasing peer-influence and different combinations of agent types with particularly suitable parcels resulted in fewer landowners deciding to sell their land, preventing sale of that land to a developer (Tables 2 and 3). We chose not to bypass this process via adjustment of parameter values, because at later simulation steps spatial sorting would result in typical concentric development patterns due to limited numbers of developable cells. By limiting model runs to six

Table 5
Differences in conversions and selling characteristics for the landowner agent types under **MEDIUM** peer-influence intensity.

	Total Converted				Converted Rate				Willingness to Sell				Decision to Sell			
	Max	Min	Sd	Avg	Max	Min	Sd	Avg	Max	Min	Sd	Avg	Max	Min	Sd	Avg
ExUrbanite	10,556	5882	1067	7317	7.06%	3.98%	0.66%	4.86%	0.48	0.37	0.024	0.42	7.95%	3.78%	0.89%	5.47%
Lifestyle	12,627	6934	1258	9980	7.02%	5.69%	0.45%	6.33%	0.49	0.38	0.025	0.44	6.35%	4.97%	0.28%	5.73%
Utilitarian	15,784	10,943	1454	13,488	10.87%	7.37%	0.89%	9.12%	0.57	0.44	0.029	0.49	19.76%	7.60%	2.32%	10.15%
Economic Maximizer	21,791	16,275	1513	19,224	16.93%	12.21%	1.23%	14.47%	0.63	0.48	0.052	0.55	21.98%	15.42%	1.45%	18.39%

simulation steps, we were able to identify the short-term micro changes that occur, and the potential processes driving changes that would otherwise become invisible due to eventual saturation of urbanization resulting from high development pressure. Hence, our model and experimental setup led to the identification of a subtle spatial process with important effects on development patterns.

Our results also display the pronounced effect of peer-influence on the spatial configuration of urbanization. Since the majority of the agents in our system were not profit motivated, willingness decreased when factoring in the generally low willingness to sell of neighbors, i.e., higher peer-influence of immediate spatial neighbors leads to lower landscape scale willingness to sell. Hence, neighbors acting together resulted in more contiguous developed areas (Fig. 7). From a conceptual point of view, this allowed us to analyze and visualize the inclusion of spatial neighborhood willingness to sell and to capture its moderating effect resulting in land sparing outcomes.

4.3. Model limitations

The introduction of new model functionality in the context of our simulation experiment resulted in several surprising but informative insights about the importance of landowner decision-making in the urban fringe. However, the current design and parameterization of the ABM sub-model may benefit from a better empirical foundation. As with a majority of modeling studies, this emphasizes the importance of empirical studies that can be used to drive model assumptions (Janssen & Ostrom, 2006; Smajgl, Brown, Valbuena, & Huigen, 2011). Specifically, we identified three key points that would benefit from more detailed process representation and parameterization: (1) agent type parameterization and allocation, (2) model representation of peer-influence, and (3) factors included in the decision-making process.

4.3.1. Agent type parameterization and allocation

The survey used to parameterize our agent types focused on woodland owners only (BenDor et al., 2014). However, we used the survey findings to define the parameters of all landowners on parcels including other land-cover types. Also, in the absence of empirical evidence of the landowners' spatial distribution in the study system, we allocated landowner types randomly in the landscape. We addressed the latter by including the effect of the random landowner distribution in the landscape as one component of our sensitivity analysis. To address the former, more empirical studies are needed to better understand decision-making of heterogeneous landowner types.

4.3.2. Model representation of peer-influence

In our current model implementation, peer-influence is represented as an averaging of WTS over the spatial neighborhood of the focal parcel – a simplified representation due to the lack of empirical data on social networks in the study area. While this component of the modeling framework provides the algorithms to connect a focal parcel (and its actor) to a flexible number of parcels (and the corresponding actors) through their identifiers, it is a highly simplified representation of peer-influence with limited explanatory power. An empirically based parameterization that goes beyond the immediate spatial neighborhood and a dynamic model representation of network structure (e.g., Fischer et al., 2013) are important next steps to improve the explanatory power of our modeling framework.

4.3.3. Decision-making process

The current modeling framework does not include a process representation for the effect of land prices on WTS and actor decision-making in general. While many studies exist that analyze the effect of land prices on land-use change (e.g., Filatova et al., 2009; Ligmann-Zielinska, 2009; Magliocca et al., 2011), our intention was to add complementary components (i.e., additional values and beliefs) to model implementations of the decision-making process. An important next step would be to combine our work with process representations for consideration of land prices in decision-making.

5. Conclusions

We developed the hybrid FUTURES-ABM framework for modeling development processes in the urban fringe including landowner decision-making at the parcel level and peer-influence of a spatial neighborhood on this decision-making process. We used existing modeling approaches and conceptual frameworks, and designed FUTURES-ABM in a generic manner to allow for transferability to other study regions. The results of our simulation experiment for Cabarrus County, North Carolina, displayed the emergence of spatial development patterns caused by the complex spatial relationships between parcel-level decision-making, the heterogeneous seller agents, and peer-influence. Our results also suggest that local patterns may deviate from 'optimal' environmental conditions due to variation in willingness to sell and the effect of peer-influence. Empirical evidence suggests that trade-offs between the production of land influences land sale, however land attachment also contributes to individual utility resulting in maintenance of patches of forest and farmland (BenDor et al., 2014; Mullendore et al., 2015). Questions remain as to whether such remnant undeveloped land will stay non-urban given retirement and inheritance of land over time (Butler and Leatherberry, 2004). By incorporating an ABM into an established CA framework, we have been able to demonstrate how the peer-influence amongst landowners can shape future urban growth patterns.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2018.09.023.

References

An, L. (2012). Modeling human decisions in coupled human and natural systems: Review of agent-based models. *Ecological Modelling, 229*, 25–36. https://doi.org/10.1016/j.ecolmodel.2011.07.010.

Barnard, C. H., & Butcher, W. R. (1989). Landowner characteristics: A basis for locational decisions in the urban fringe. *American Journal of Agricultural Economics, 71*(3), 679. https://doi.org/10.2307/1242023.

Barredo, J. I., Kasanko, M., McCormick, N., & Lavalle, C. (2003). Modelling dynamic spatial processes: Simulation or urban future scenarios through cellular automata. *Landscape and Urban Planning, 64*(3), 145–160. https://doi.org/10.1016/S0169-2046(02)00218-9.

BenDor, T., Shoemaker, D. A., Thill, J.-C., Dorning, M. A., & Meentemeyer, R. K. (2014). A mixed-methods analysis of social-ecological feedbacks between urbanization and forest persistence. *Ecology and Society, 19*(3), 3. https://doi.org/10.5751/ES-06508-190303.

Brown, D. G., Page, S., Riolo, R., Zellner, M., & Rand, W. (2007). Path dependence and the validation of agent-based spatial models of land use. *International Journal of Geographical Information Science, 19*(2), 153–174. https://doi.org/10.1080/13658810410001713399.

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*(4), 247–263.

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. https://doi.org/10.2337/dc11-1153.
Brown, D. G., Robinson, D. T., An, L., Nassauer, J. I., Zellner, M., Rand, W., ... Wang, Z. (2008). Exurbia from the bottom-up: Confronting empirical challenges to characterizing a complex system. *Geoforum, 39*(2), 805–818. https://doi.org/10.1016/j.geoforum.2007.02.010.
Butler, B. J., & Leatherberry, E. C. (2004). America's family forest owners. *Journal of Forestry, 102*(7).
Chen, X., Vina, A., Shortridge, A., An, L., & Liu, J. (2014). Assessing the effectiveness of payments for ecosystem services: An agent-based modeling approach. *Ecology and Society, 19*(1), 7.
Delmelle, E. C., Zhou, Y., & Thill, J.-C. (2014). Densification without growth management? Evidence from local land development and housing trends in Charlotte, North Carolina, USA. *Sustainability, 6*(6), 3975–3990. https://doi.org/10.3390/su6063975.
Delre, S. A., Jager, W., Bijmolt, T. H. A., & Janssen, M. A. (2010). Will it spread or not? The effects of social influences and network topology on innovation diffusion. *Journal of Product Innovation Management, 27*(2), 267–282. https://doi.org/10.1111/j.1540-5885.2010.00714.x.
Dorning, M. A., Koch, J., Shoemaker, D. A., & Meentemeyer, R. K. (2015). Simulating urbanization scenarios reveals tradeoffs between conservation planning strategies. *Landscape and Urban Planning, 136*, 28–39. https://doi.org/10.1016/j.landurbplan.2014.11.011.
Filatova, T. (2015). Empirical agent-based land market: Integrating adaptive economic behavior in urban land-use models. *Computers, Environment and Urban Systems, 54*, 397–413. https://doi.org/10.1016/j.compenvurbsys.2014.06.007.
Filatova, T., Parker, D., & Van Der Veen, A. (2009). Agent-based urban land markets: Agent's pricing behavior, land prices and urban land use change. *Journal of Artificial Societies and Social Simulation, 12*(1), 3.
Filatova, T., Voinov, A., & van der Veen, A. (2011). Land market mechanisms for preservation of space for coastal ecosystems: An agent-based analysis. *Environmental Modelling and Software, 26*(2), 179–190. https://doi.org/10.1016/j.envsoft.2010.08.001.
Fischer, P., Korejwa, A., Koch, J., Spies, T. A., Olsen, C., White, E., & Jacobs, D. (2013). Using the Forest, People, Fire agent-based social network model to investigate interactions in social-ecological systems. *Practicing Anthropology, 35*(1), 8–13. https://doi.org/10.17730/praa.35.1.w7348256k283t131.
Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., & Railsback, S. F. (2010). The ODD protocol: A review and first update. *Ecological Modelling, 221*(23), 2760–2768. https://doi.org/10.1016/j.ecolmodel.2010.08.019.
Groeneveld, J., Müller, B., Buchmann, C. M., Dressler, G., Guo, C., Hase, N., ... Schwarz, N. (2017). Theoretical foundations of human decision-making in agent-based land use models – A review. *Environmental Modelling & Software, 87*, 39–48. https://doi.org/10.1016/j.envsoft.2016.10.008.
Herold, M., Goldstein, N. C., & Clarke, K. C. (2003). The spatiotemporal form of urban growth: Measurement, analysis and modeling. *Remote Sensing of Environment, 86*(3), 286–302. https://doi.org/10.1016/S0034-4257(03)00075-0.
Huang, Q., Parker, D. C., Filatova, T., & Sun, S. (2014). A review of urban residential choice models using agent-based modeling. *Environment and Planning B: Planning and Design, 40*, 1–29. https://doi.org/10.1068/b120043p.
Huff, E. S., Leahy, J. E., Hiebeler, D., Weiskittel, A. R., & Noblet, C. L. (2015). An agent-based model of private woodland owner management behavior using social interactions, information flow, and peer-to-peer networks. *PLoS One, 10*(11), 1–21. https://doi.org/10.1371/journal.pone.0142453.
Irwin, E., Jayaprakash, C., & Munroe, D. (2009). Towards a comprehensive framework for modeling urban spatial dynamics. *Landscape Ecology, 24*(9), 1223–1236. https://doi.org/10.1007/s10980-009-9353-9.
Jager, W., Janssen, M. A., De Vries, H. J. M., De Greef, J., & Vlek, C. A. J. (2000). Behaviour in commons dilemmas: Homo economicus and Homo psychologicus in an ecological-economic model. *Ecological Economics, 35*(3), 357–379.
Janssen, M. A. (2011). *Targeting individuals to catalyze collective action in social networks. 2011 Annual Conference of the Computational Social Science Society of America*. Santa Fe, NM, USA: Computational Social Science Society of America.
Janssen, M. A., & Ostrom, E. (2006). Empirically based, agent-based models. *Ecology and Society, 11*(2), 37.
Kauneckis, D., & York, A. M. (2009). An empirical evaluation of private landowner participation in voluntary forest conservation programs. *Environmental Management, 44*(3), 468–484. https://doi.org/10.1007/s00267-009-9327-3.
Koch, J. (2010). *Modeling the impacts of land-use change on ecosystems at the regional and continental scale.* Kassel: kassel university press.
Koch, J., Wimmer, F., & Schaldach, R. (2018). Analyzing the relationship between urbanization, food supply and demand, and irrigation requirements in Jordan. *Science of the Total Environment, 636*, 1500–1509. https://doi.org/10.1016/j.scitotenv.2018.04.058.
Levine, J., Chan, K. M. A., & Satterfield, T. (2015). From rational actor to efficient complexity manager: Exorcising the ghost of Homo economicus with a unified synthesis of cognition research. *Ecological Economics, 114*, 22–32. https://doi.org/10.1016/j.ecolecon.2015.03.010.
Ligmann-Zielinska, A. (2009). The impact of risk-taking attitudes on a land use pattern: An agent-based model of residential development. *Journal of Land Use Science, 4*(4), 215–232.
Little, L. R., & McDonald, A. D. (2007). Simulations of agents in social networks harvesting a resource. *Ecological Modelling, 204*(3–4), 379–386. https://doi.org/10.1016/j.ecolmodel.2007.01.013.
Magliocca, N., McConnell, V., & Walls, M. (2015). Exploring sprawl: Results from an economic agent-based model of land and housing markets. *Ecological Economics, 113*, 114–125. https://doi.org/10.1016/j.ecolecon.2015.02.020.
Magliocca, N., McConnell, V. D., Walls, M. A., & Safirova, E. A. (2012a). Explaining sprawl with an agent-based model of exurban land and housing markets. *Resources for the Future*.
Magliocca, N., McConnell, V., Walls, M., & Safirova, E. (2012b). Zoning on the urban fringe: Results from a new approach to modeling land and housing markets. *Regional Science and Urban Economics*. https://doi.org/10.1016/j.regsciurbeco.2011.08.012.
Magliocca, N., Safirova, E., McConnell, V., & Walls, M. (2011). An economic agent-based model of coupled housing and land markets (CHALMS). *Computers, Environment and Urban Systems, 35*(3), 183–191. https://doi.org/10.1016/j.compenvurbsys.2011.01.002.
Manson, S. M., Jordan, N. R., Nelson, K. C., & Brummel, R. F. (2016). Modeling the effect of social networks on adoption of multifunctional agriculture. *Environmental Modelling & Software, 75*, 388–401. https://doi.org/10.1016/j.envsoft.2014.09.015.
McGarigal, K. (2015). FRAGSTATS HELP. FRAGSTATS Version 4 Documentation.
Meentemeyer, R. K., Tang, W., Dorning, M. A., Vogler, J. B., Cunniffe, N. J., & Shoemaker, D. A. (2013). FUTURES: Multilevel simulations of emerging urban-rural landscape structure using a stochastic patch-growing algorithm. *Annals of the Association of American Geographers, 103*(4), 785–807. https://doi.org/10.1080/00045608.2012.707591.
Meyfroidt, P. (2013). Environmental cognitions, land change, and social–ecological feedbacks: An overview. *Journal of Land Use Science, 8*(3), 341–367.
Mullendore, N. D., Ulrich-Schad, J. D., & Prokopy, L. S. (2015). U.S. farmers' sense of place and its relation to conservation behavior. *Landscape and Urban Planning, 140*, 67–75. https://doi.org/10.1016/j.landurbplan.2015.04.005.
Nassauer, J. I., Wang, Z., & Dayrell, E. (2009). What will the neighbors think? Cultural norms and ecological design. *Landscape and Urban Planning, 92*(3), 282–292. https://doi.org/10.1016/j.landurbplan.2009.05.010.
National Research Council. (2014). Advancing land change modeling: Opportunities and research requirements. Washington, DC.
O'Sullivan, D., Evans, T., Manson, S., Metcalf, S., Ligmann-Zielinska, A., & Bone, C. (2015). Strategic directions for agent-based modeling: Avoiding the YAAWN syndrome. *Journal of Land Use Science, 11*(2), 177–187. https://doi.org/10.1080/1747423X.2015.1030463.
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*(2), 314–337. https://doi.org/10.1111/1467-8306.9302004.
Petrasova, A., Petras, V., van Berkel, D., Harmon, B. A., Mitasova, H., & Meentemeyer, R. K. (2016). Open Source Approach to Urban Growth Simulation. In The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (pp. 953–959). Prague, Czech Republic. http://doi.org/10.5194/isprsarchives-XLI-B7-953-2016.
Pickard, B. R., van Berkel, D., Petrasova, A., & Meentemeyer, R. K. (2017). Forecasts of urbanization scenarios reveal trade-offs between landscape change and ecosystem services. *Landscape Ecology, 32*(3), 617–634. https://doi.org/10.1007/s10980-016-0465-8.
Pyle, G. F. (1989). Physician office locations within Charlotte, North Carolina. *Southeastern Geographer, 29*(2), 118–135.
Robinson, D. T., Brown, D. G., Parker, D. C., Schreinemachers, P., Janssen, M. A., Huigen, M., ... Barnaud, C. (2007). Comparison of empirical methods for building agent-based models in land use science. *Journal of Land Use Science, 2*(1), 31–55. https://doi.org/10.1080/17474230701201349.
Rounsevell, M. D. A., Arneth, A., Brown, D. G., de Noblet-Ducoudré, N., Ellis, E., Finnigan, J., … Young, O. (2012). Incorporating human behaviour and decision making processes in land use and climate system models. GLP Report No. 7. São José dos Campos.
Schlüter, M., Baeza, A., Dressler, G., Frank, K., Groeneveld, J., Jager, W., ... Wijermans, N. (2017). A framework for mapping and comparing behavioural theories in models of social-ecological systems. *Ecological Economics, 131*, 21–35. https://doi.org/10.1016/j.ecolecon.2016.08.008.
Smajgl, A., Brown, D. G., Valbuena, D., & Huigen, M. G. A. (2011). Empirical characterisation of agent behaviours in socio-ecological systems. *Environmental Modelling and Software, 26*(7), 837–844. https://doi.org/10.1016/j.envsoft.2011.02.011.
Smith, J. W., Smart, L. S., Dorning, M. A., Dupéy, L. N., Méley, A., & Meentemeyer, R. K. (2017). Bayesian methods to estimate urban growth potential. *Landscape and Urban Planning, 163*, 1–16. https://doi.org/10.1016/j.landurbplan.2017.03.004.
Sohl, T., Dornbierer, J., Wika, S., Sayler, K., & Quenzer, R. (2017). Parcels versus Pixels: Modeling agricultural land use across broad geographic regions using parcel-based field boundaries. *Journal of Land Use Science, 12*(4), https://doi.org/10.1080/1747423X.2017.1340525.
United Nations, & Department of Economic and Social Affairs (Population Division). (2015). World Population Prospects: The 2015 Revision. New York.
United States Census Bureau. (2017). The South Is Home to 10 of the 15 Fastest-Growing Large Cities. https://www.census.gov/newsroom/press-releases/2017/cb17-81-population-estimates-subcounty.html (accessed January 1, 2017).
Valbuena, D., Verburg, P. H., Bregt, A. K., & Ligtenberg, A. (2010). An agent-based

approach to model land-use change at a regional scale. *Landscape Ecology, 25*(2), 185–199. https://doi.org/10.1007/s10980-009-9380-6.

Verburg, P. H., Kok, K., Pontius, R. G., & Veldkamp, A. (2006). Modeling land-use and land-cover change. In E. F. Lambin, & H. J. Geist (Eds.). *Land-Use and Land-Cover Change. Global Change – The IGBP Series* (pp. 117–135). Berlin, Heidelberg: Springer. https://doi.org/10.1007/3-540-32202-7_5.

White, R., & Engelen, G. (1993). Cellular automata and fractal urban form: A cellular modelling approach to the evolution of urban land-use patterns. *Environment and Planning A, 25*(8), 1175–1199. https://doi.org/10.1068/a251175.

Zhang, Q., Vatsavai, R. R., Shashidharan, A., & van Berkel, D. B. (2016). Agent based urban growth modeling framework on Apache Spark. *Proceedings of the 5th ACM SIGSPATIAL International Workshop on Analytics for Big Geospatial Data* (pp. 50–59). ACM.