Environment and Planning B: Planning and Design 2014, volume 41, pages 661 – 689

doi:10.1068/b120043p

A review of urban residential choice models using agent-based modeling

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Received 1 November 2012; in revised form 3 June 2013; published online 22 November 2013

Abstract. Urban land-use modeling methods have experienced substantial improvements in the last several decades. With the advancement of urban land-use change theories and modeling techniques, a considerable number of models have been developed. The relatively young approach, agent-based modeling, provides urban land-use models with some new features and can help address the challenges faced by traditional models. Applications of agent-based models to study urban dynamics have increased steadily over the last twenty years. To offer a retrospective on the developments in agent-based models (ABMs) of urban residential choices, we review fifty-one relevant models that fall into three general categories: (i) urban land-use models based on classical theories; (ii) different stages of the urbanization process; and (iii) integrated agent-based and microsimulation models. We summarize and compare the main features of these fifty-one models within each category. This review focuses on three fundamental new features introduced byABMs. The first is agent heterogeneity with particular attention to the method of introducing heterogeneity in agents' attributes and behaviors. The second is the representation of land-market processes, namely preferences, resources constraints, competitive bidding, and endogenous relocation. The third is the method of measuring the extensive model outputs. In addition, we outline accompanying challenges to, and open questions for, incorporating these new features. We conclude that, by modeling agent heterogeneity and land markets, and by exploiting a much broader dimension of output, we will enhance our understanding of urban land-use change and are hopefully able to improve model fitness and robustness.

Keywords: agent heterogeneity, land market, agent-based modeling, segregation model, residential choice, microsimulation, output evaluation

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1 Introduction

In the field of urban land-use-change simulation, in a growing volume of literature, an agent-based modeling approach is applied to construct models, due to its ability to represent an individual's decision-making process and mobility from the bottom up (An, 2012; Haase and Schwarz, 2009; Kennedy, 2012; Macy and Willer, 2002; Matthews et al, 2007; O'Sullivan et al, 2012; Parker et al, 2003; Torrens, 2012). Along a continuum from theoretical to empirical, at one end, purely theoretical and stylized models are developed to simulate classical urban residential problems, such as monocentric patterns of cities and segregation of residents (Benenson and Torrens, 2004a; Crooks et al, 2008); at the other end, empirical models driven by extensive spatial and nonspatial data are constructed to simulate residential choices within a complex urban system (Birkin and Wu, 2012; Zaidi and Rake, 2001). Between the two extremes, a number of models, which are based partly on empirical situations and partly on theoretical findings, are built to simulate urban residential phenomena, such as gentrification and urban sprawl.

The advantage of agent-based modeling is that it can move beyond some restrictive assumptions of other modeling techniques in accommodating bounded rationality, heterogeneity among agents, and out-of-equilibrium dynamics and interactions, giving modelers much more freedom in model design. While the importance of these features in general has been extensively discussed (An, 2012; Arthur, 1999; Axtell, 2000; Bonabeau, 2002; Epstein, 1999; Manson et al, 2012; O'Sullivan et al, 2012; Parker et al, 2003), three aspects that are vital for modeling urban phenomena have not been reviewed thoroughly. The first is agent heterogeneity (AH). As Irwin (2010) acknowledged, AH, which is defined as "key differences among individual households, firms or other agents, e.g., differences in preferences, wealth, technology or expectations" (page 69), is an important driving force for spatial land-use dynamics. However, there is no common agreement on how to either incorporate AH or evaluate its effects on the aggregated urban dynamics and patterns, especially with multiple numbers of heterogeneous agent attributes. The second is the extent of land-market representation (LMR), which influences residential choice and consequent land-use change (Parker et al, 2012a). The degree of representation of land-market processes in existing models varies greatly. Yet, progress in representing land-market processes and their effects on spatial and socioeconomic outcomes has not been reviewed fully. The third essential feature is methods to measure the variety of outcomes resulting from AH and LMR. Agent-based models (ABMs) provide both aggregated spatial and socioeconomic outcomes and disaggregated outcomes at the agent level, which demand not only traditional spatial metrics but also other analysis methods (Herold et al, 2005; Parker and Meretsky, 2004). Moreover, the choice of these three aspects has been driven by their close intrinsic relationship. Specifically, inclusion of higher levels of LMR adds more dimensions of agents' heterogeneity (eg, income, credit, mortgage, risk attitude, bidding power). As additional functionalities and attributes are introduced, the set of output measures needs to be aligned to capture the changing patterns of macrodynamics.

In light of the growth of applications in agent-based urban land-use-change models, we review recent urban agent-based residential choices models. Our main objective is to survey the literature on the simulation of urban residential choice rooted in agent-based modeling, with a focus on the progress of the representation of AH, LMR, and output measurement (OM). In addition, we provide general discussion of the research gaps that remain in spite of this progress in order to improve model development and model authenticity.

In order to guarantee comparability among models, three criteria are used to select models: (1) their main objective is to simulate residential choice in the context of urban development, (2) they are spatially explicit and based on agent-based modeling techniques or microsimulation (MSM) modeling; and (3) their results are published in peer-reviewed journals, book chapters, or conference proceedings.

Using these three criteria, fifty-one models were reviewed, and three main research domains were identified. Three aspects of models in each research domain are summarized and compared in section 2. In section 3 the three distinctive features—AH, LMR, and OM—are discussed in detail. In the final section we offer a brief summary and discuss general outstanding challenges in this area.

2 Modeling urban phenomena with ABMs: three research domains

Following the continuum defined by Parker et al (2002), which runs from purely theoretical to intensively empirical models, we identify three research domains across the fifty-one reviewed models: (i) variations of classical stylized models that are commonly constructed using classical theories (eg, Schelling's segregation model and the Alonso–Von Thünen model); (ii) models simulating different stages of the urbanization process that combine theories and empirical findings (eg, urban sprawl, urban shrinkage, urban expansion, and gentrification); and (iii) microsimulation of urban systems integrated with ABMs that are largely driven by empirical data to replicate details of a specific case study.

2.1 Classical models and variations

A series of stylized ABMs have been developed to investigate questions central to the development of urban form—how patterns of residential segregation, land use, and land value emerge. These ABMs often build on paradigmatic theoretical precedents. In this section, we review two families of such models: Schelling-style residential segregation, and extensions of the monocentric bid-rent model.

2.1.1 *Schelling's segregation model and its variations*

Residential segregation is a common phenomenon worldwide (Clark, 1986; Galster, 1988; Huttman et al, 1991; Johnston et al, 2007). It is an outcome of residential choices due to heterogeneity among resident types, their preferences to be near others of their type, and locational heterogeneity. In 1970 Schelling and Sakoda independently proposed similar models to explain residential segregation (Benenson and Torrens, 2004a). In these models, space is represented by a grid. Black or white households tend to migrate to a place where local residential familiarity in the neighborhood is acceptable when dissatisfaction in the current neighborhood increases. Households' attitudes toward a household of another color can be attractive, neutral, or avoidant. This classical stylized model is designed to be intentionally primitive. The number of households of each color is constant and equal. Their migration decisions are based upon evaluating the residential dissonance measured by the number of other-type households within a first-order queen's neighborhood (ie, 3×3 cells surrounding a host cell).

These models demonstrate that segregation patterns can emerge from individual migration decisions, even with a modest preference for similar neighbors. In the last few decades since the model was proposed, improvements in computing capacity and technology have enabled researchers to explore and extend the basic results in various ways. In fact, the effects on segregation have been evaluated by changing almost all the input parameters, individually and in combination (table 1). The main extensions include (but are not limited to):

- The division of space is changed from a traditional grid to a Voronoi partition (Benenson, 1999; Benenson et al, 2002; Omer, 2005) or a vector layer (Crooks, 2010).
- The representation of space varies from homogeneous and featureless to heterogeneous based on empirical conditions (Yin, 2009).
- The two traditional types of residents (ie, black and white) are extended to three groups, derived from an empirical survey, in Los Angeles (Clark and Fossett, 2008), four groups

Table 1. Comparison of Schelling's segregation model and its variations.

Label	Space	Groups of households	Number of households within group	Neighborhood	Migration strategies	Extra factors
Laurie and Jaggi (2003)	grid	2	equal	8 (first-order queen's neighborhood)	satisficer	
O'Sullivan et al (2003)	grid	2	equal	distance (1–5)	satisficer	
Fossett and Waren (2005)	grid	2	equal	2 levels of neighbors	satisficer	
Fossett and Dietrich (2009)	grid	2	uneven	48 (7×7)	maximizer	
Clark and Fossett (2008)	grid	2	uneven	various types	maximizer	
Wasserman and Yohe (2001)	grid	3	uneven	40 neighbors	maximizer	income, housing quality
Crooks (2010)	grid	2	equal	exponent decayed	satisficer	location, public good
Benenson and Hatna (2011); Hatna and Benenson (2012)	vector	2 or 4	uneven (empirical)	buffering and constrained by natural barrier	satisficer	natural barrier
Omer (2005)	grid	2	uneven	5×5	satisficer	
Torrens (2007)	vector	4	equal	8 (first-order queen's neighborhood)	satisficer	
Benenson et al (2002)	grid	3	uneven	regional and local	satisficer	wealth, inertia, property type
Benenson (1999)	Voronoi partition	continuous	uneven (empirical)	distance and street barrier	satisficer	housing style
Yin (2009)	grid or vector	continuous	empirical	queen's neighborhood or buffering and street barrier	satisficer	income, housing value, cultural code
Bruch and Mare (2006; 2009); Xie and Zhou (2012)	grid and empirical	2	uneven	block boundary	satisficer	housing sale price
Crooks (2006)	grid	2	equal	5×5	satisficer	
Ellis et al (2011)	grid	6	uneven	second-order queen's neighborhood	satisficer	

in London (Crooks, 2010), and two-level hierarchical groups (two top groups and two subgroups rather than each top group) in Tel Aviv (Omer, 2005). Additionally, Ellis et al (2011) introduced another group of households, mixed-race households, in their model. Accordingly, residents' preferences for a given group rather than other groups are not equal and can vary from group to group.

- In addition to the original eight neighbors, various shapes and sizes of neighborhoods are examined (Fossett and Dietrich, 2009; Laurie and Jaggi, 2003). A hierarchical neighborhood (O'Sullivan et al, 2003), neighborhoods considering the barrier effect of natural elements (eg, a river) (Crooks, 2010) and streets (Benenson, 1999), and a block neighborhood, defined by the census (ie, census block) (Yin, 2009), are also implemented.
- The migration strategies are distinguished between 'satisficer' and 'maximizer' (Benenson and Hatna, 2011). The former is willing to accept any potential property with higher utility or satisfying level, while the latter only move to the location providing the highest utility or satisfying level.
- Besides ethnic composition, more driving forces for segregation, such as income and house quality (Clark and Fossett, 2008), attractiveness of public goods (Wasserman and Yohe, 2001), cultural differences (Benenson, 1999), property type and agent's inertia (Torrens, 2007), are simulated to replicate the real conditions.

2.1.2 *The Von Thünen–Alonso model and its variations*

In addition to residential segregation, researchers have developed models to explain urban spatial structure and the location of households and firms. This stream of studies is rooted in location theory. During the 19th century, Von Thünen (1966) developed the conceptual basis for economic bid-rent theory to account for the spatial distribution of agricultural activities around the central market. In this model, decision makers bid for the land around the central market depending on their transport costs, production costs, and market prices of agricultural goods. The land is allocated to the highest bidder. Resulting from this process, concentric rings of different crops form around the market center based on differences in the costs and prices of agricultural goods.

The model was extended and applied to the urban context by Alonso (1964), Muth (1969), and Mills (1972). In the monocentric city model, a central business district (CBD) is located in the center of the city, which serves as a proxy for access to cultural and business opportunities. Residents make bidding choices that maximize their utilities under the tradeoff between commuting and housing costs. Land is allocated to the resident who provides the highest bid. Spatial equilibrium culminates in a declining trend of population density, land value, and housing price with distance from the CBD (Anas et al, 1998; Parker and Filatova, 2008). Analytical extensions of the original Alonso model have been developed by incorporating developers' decisions on development density (Mills, 1972; Muth, 1969), open-space amenities, and spatial externalities (Caruso et al, 2007; Cavailhès et al, 2004; Irwin and Bockstael, 2002; Wu and Plantinga, 2003). This field has developed further to create polycentric extension to the original monocentric city model (see Fujita and Ogawa, 1982; Fujita and Thisse, 2002; Harris, 1985; Munroe, 2007; Ogawa and Fujita, 1980 for a review).

In addition to spatial analytical models, ABMs are used to extend the traditional monocentric city model by allowing interactions of heterogeneous agents and market disequilibrium in the model (table 2):

- The most common feature among this category of model (table 2) is a price-formation function. This implies that each local transaction price emerges from interactions between buyers and sellers, rather than a fixed land rent being imposed on the model exogenously.

Table 2. Representative features of the Von Thünen–Alonso model and its variations.

	Price formation	Bidding or negotiation	Spatial externalities	Agent hetero-geneity	Mono-centric and leapfrog	Others
Crooks (2006)	yes	yes	na	yes	na	Interactions with firms, dynamic attributes evolves with time
Filatova et al (2009a; 2011a)	yes	yes	yes	yes	both	Heterogeneous risk attitudes
Gilbert et al (2009)	yes	no	no	yes	no	Realtor, time dynamics
Magliocca et al (2011)	yes	yes	no	yes	both	Building heterogeneity, developer
Chen et al (2011)	yes	yes	no	yes	both	Optimal timing of development
Ettema (2011)	yes	yes	no	yes	no	Relocation, perceptions of housing market probabilities

na—not applicable.

- When simulating endogenous transaction prices, the majority of models have an endogenous willingness-to-pay (WTP) function for buyers, which depends on both spatial and agent-level factors. In the bid-rent model developed by Crooks (2006), the bidding price is formed using residents' income and preference heterogeneity as well as travel cost and required space. In the ALMA model (Filatova et al, 2009a), buyers' WTP is based on their utilities (calculated by preferences for open-space amenity and proximity to the CBD), transport cost, budgets, and nonhousing costs. Gilbert et al (2009) assume buyers will purchase the most expensive property they can afford, assuming that housing price reflects the house quality. The transaction prices are affected by buyers' heterogeneous incomes and preferences. In the CHALMS model (Magliocca et al, 2011), households' bidding prices depend on the characteristics of the house, lot size, travel cost, households' preferences for housing type and developers' asking price. In the model developed by Chen et al (2011), the bidding price is not only dependent on the number of competitors but also on the income distribution, which evolves over time. The agent-based housing-market model proposed by Ettema (2011) adopted an alternative price-formation strategy. Rather than simulating explicit WTPs or WTAs (willingness to accept), a buyer (or a seller) formulates a specific probability of buying (or selling) the property at a given listed price. These perceptions of housing-market probabilities are updated over time based on negotiation in the market, and affect resulting housing prices.
- These price-formation functions allow for inclusion of a certain level of spatial and AH, such as differences in locations, housing types, preferences, incomes, and risk attitudes. Thus, all the models have the feature of AH (table 2).
- Models are able to simulate expectation formations of future prices. For example, Chen et al (2011) simulated landowners' expected value of land based on the current agricultural rent and future return from selling the land. In CHALMS both farmers and developers employ various prediction strategies to form their expectations of future land and housing

prices, respectively (Magliocca et al, 2011). In Ettema's model (2011), the probability of selling or buying a house is determined by the expected return for that house within a given period and updated over time by a Bayesian learning procedure based on past transactions.

- Additionally, spatial heterogeneity and AH enable models to simulate other complex behaviors of buyers and processes of market, for example:
  - ◊ Bidding prices are further adjusted by different market conditions. In ALMA, bidding prices are adjusted by the relative market power of buyers and sellers (ie, excess of demand or supply) (Filatova et al, 2009a). In the model developed by Chen et al (2011), the bidding prices are influenced by the number of participants in the competition. In CHALMS, bidding prices of consumers are also impacted by a housing market competition factor, based on number of available houses relative to the the number of buyers (Magliocca et al, 2011).
  - ◊ Heterogeneous risk attitudes can affect the patterns of land development and land rent, as indicated by the ALMA model (Filatova et al, 2009b; 2011a).
  - ◊ The effects of economic incentives (eg, tax), on protecting coastal environment are demonstrated in ALMA (Filatova et al, 2011b).
- In addition to the classical result of declining house price with distance from the CBD, three models are able to simulate leapfrog development in the urban–rural fringe, although they have adopted different theories to explain this pattern. In ALMA (Filatova et al, 2009a), the tradeoff between an open-space amenity (ie, spatial externality) and proximity to the CBD is the main driver for the fragmented development in the exurban area. In CHALMS (Magliocca et al, 2011), the leapfrog development emerges from various sources of spatial homogeneity and AH (including agricultural productivity of parcels, house size, lot size, households' incomes and preferences for housing types, and farmers' and developers' expectations of future prices) and market interactions between farmers, developers, and households in the land and housing market. In the model developed by Chen et al (2011), leapfrog development arises from spatial heterogeneity of competition and AH of income that give priorities to richer households for locations with less competition and that are less constrained by commuting cost. In the real world a combination of these factors is likely behind observed leapfrog-development patterns.
- Some models extend the traditional abstract initial landscape configuration by incorporating empirical spatial elements. In ALMA-C, a coastal area with higher amenity and coastal hazard levels is simulated using the empirical finding for coastal areas of the Netherlands (Filatova et al, 2011a; 2011b). In CHALMS, the land surrounding the CBD is divided into fifty farms, whose attributes are derived from census data in suburban counties in the Mid-Atlantic region. Due to the empirical configuration of the landscape, the final spatial pattern of development diverges from the patterns of the classical monocentric model (Magliocca et al, 2011). The model developed by Crooks (2006) moves away from the restrictive assumption of centralized employment by introducing heterogeneous firms across the landscape. The location of residents and firms is determined by the competition between firms and residents and feedbacks between agents and the environment.

2.2 Different stages of the urbanization process

Due to the differences in their local physical and socioeconomic environment, cities experience specific urbanization processes and face distinctive challenges brought by these given contexts. ABMs are developed to capture the residential choices in different processes of urbanization. These models are usually based partially on theoretical findings and partially on empirical data from specific urbanization processes. For instance, Ligmann-Zielinska (2009) developed an ABM to evaluate the impacts of developers' risk attitudes on the fragmentation of development in a hypothetical urban area. Heckbert and Smajgl (2005) developed regional projects by incorporating various empirical factors to simulate residential choices in Austrian cities. Thus, urban residential-choice models that simulate different stages of the urbanization process vary greatly. Yet, there are some common characteristics which can be summarized as follows:

- The manifestation of urbanization is different between developing countries and developed countries. Both the driving forces of urbanization and the patterns of land-use change can vary substantially, for example:
  - ◊ In developing countries, the growth of informal settlements, which are established without planning regulations and basic facilities, is modeled in Dar es Salam, Tanzania (Augustijn-Beckers et al, 2011). Peripherisation, defined as the "formation of low-income residential areas in the peripheral ring of the city and a perpetuation of a dynamic core–periphery spatial pattern" (Barros, 2012, page 571), is simulated in Latin American cities. The rapid urbanization of a densely rural population in a newly developed region, known as Desakota, is simulated in China (Xie et al, 2007).
  - ◊ In developed countries, different phenomena are under inspection. For instance, models are proposed to test theoretical hypotheses of gentrification theory (Diappi and Bolchi, 2008) and in empirical contexts [eg, in east London (O'Sullivan, 2002), Boston (Jackson et al, 2008), and Salt Lake City (Torrens, 2007)].
  - ◊ The understanding of another urbanization phenomena, urban sprawl (or sub-urbanization), is also facilitated by ABMs. Urban sprawl in Southeastern Michigan is simulated by the SOME and DEED models developed by Brown and his colleagues (Brown et al, 2004; 2008; Fernandez et al, 2005; Rand et al, 2002; Robinson and Brown, 2009; Zellner et al, 2010). Other urban sprawl models are developed for the Vienna region (Loibl and Toetzer, 2003; Loibl et al, 2007), northwest of Lyons, Boulder County, CO (Yin and Muller, 2007), and the Brussels periurban area (Caruso et al, 2005). The feedbacks between segregation and suburbanization are also analyzed by a stylized ABM (Jayaprakash et al, 2009).
  - ◊ Urban shrinkage, which is characterized by a large amount of residential vacancies resulting from an oversupply of dwellings, is also a hot topic among modelers. For instance, residential mobility in the shrinking city of Leipzig in eastern Germany is simulated by an ABM called RESMOBcity (Haase et al, 2010).
- The majority of models in this category are policy oriented. In other words, policy and planning strategies and their influence on urban physical morphology, socioeconomic outcome, and environmental consequence are evaluated via what-if scenarios in most empirical applications. For instance, land-use strategies encouraging compact development are examined by an ABM that has the ability to measure the compactness of the city from the perspective of its transport efficiency, energy consumption, and residents' welfare (Kii and Doi, 2005). The influence of residential, commercial, and industrial development on the forest ecosystem under different management strategies is evaluated in Texas, USA (Monticino et al, 2007). Sustainable development strategies are embedded in an ABM to regulate agents' behavior in a rapidly expanding city in China (Li and Liu, 2008). Belief in and preferences for spatial objects from multiple actors are simulated in a hypothetical planning scenario in the Netherlands to support decision making of spatial planners (Ligtenberg et al, 2001; 2004). And an urban regeneration policy that intends to encourage social mixing in the UK is simulated in an agent-based housing-choice model to evaluate its effects on the vitality of the housing market and availability of jobs (Jordan et al, 2011; 2012).

- In order to cope with the data limitations and complexity in individual urbanization processes, an ABM is commonly integrated with other modeling techniques. For example, a hybrid model combining ABM, logistic regression, and neighborhood effects is used to simulate the impacts of land-use change on agricultural soil, noise pollution and quality of life in the Municipality of Koper, Slovenia (Robinson et al, 2012). Another model integrating multiobjective land-use allocation and agent-based modeling is applied to evaluate the influences of suburbia and exurbia under different planning situations in a community in Washington State, USA (Ligmann-Zielinska and Jankowski, 2007, 2010). Urban growth for the Phoenix metropolitan region of the United States is predicted by a hybrid of agent-based modeling and spatial regression (Tian et al, 2011). And the new version of SLUCEII-ABM integrates individuals' behaviors in land markets and land management by using an ABM and an ecosystem model BIOME-BGC to evaluate the dynamic land-cover and land-use change and subsequent influence on carbon storage and flux (Parker et al, 2012b; Robinson et al, 2013).

2.3 Agent-based and microsimulation modeling

According to the International Microsimulation Association (2012), MSM is defined as a modeling technique that operates at the level of individual units such as persons, households, vehicles or firms. Each individual contains various unique attributes and follows a set of behavioral rules. MSM was introduced in 1950s by Orcutt (1957) in an attempt to develop an alternative approach to traditional aggregated models to model the diversity of the US economic system (Clarke and Holm, 1987). This technique has been increasingly applied in simulations of tax benefit, social and fiscal policy, demographic dynamic, health, traffic flows, firms, and enterprises (Birkin and Wu, 2012; Zaidi and Rake, 2001).

MSM is closely parallel to two other individual-level modeling approaches: individual-based modeling in ecology (see Bousquet and Le Page, 2004; Grimm and Railsback, 2005 for a review), and agent-based modeling. Both MSMs and ABMs simulate individuals' decision-making processes based on agents' heterogeneous attributes and their interactions with the environment and other individuals. MSM is a more inductive approach and relies heavily on methods that infer, from aggregated patterns to individual agents, such as regression analysis and probabilistic modeling (Mahdavi et al, 2007). In contrast, ABMs typically combine inductive and deductive approaches (Axelrod, 1997; Nolan et al, 2009) and simulate aggregated pattern as an emergent cumulative effect of individual behaviors. In addition, the specialty of MSM is to predict the impacts of policy changes on a population of agents based primarily on historic data, which is used for fitting the statistical models. In contrast, ABMs are more suitable when new dynamics, critical transitions, and switching to different regimes (economic crisis, housing bubble) are expected. This is due to the fact that individual agents' behaviors can be driven by adaption and evolutionary learning rooted in artificial intelligence, which leads to the emergence of new strategies and changes in preferences and risk attitudes. However, as Birkin and Wu (2012) acknowledge, the boundary between MSM and empirical spatial ABMs is likely to fade away over time, and the relationship between the two approaches is better described as complementary. In summary, incorporating MSM into ABMs will be helpful in accommodating a broad dimension of AH (eg, demographic attributes) within the model and enhancing the predicative power of agent-based modeling.

A series of empirical models integrating MSM with agent-based modeling has been developed to project urban system dynamics (table 3). By reviewing these models, some common features can be identified:

- Most models (see table 3) have multiple types of agents. The model will simulate the moving and residential choice of households, the location and real-estate-type choice of

Table 3. Microsimulation models containing urban residential location and their characteristics.

References	Model name	Study area	Agent type	Transport pattern	Policy scenarios	Environ-mental effects
Ettema et al (2007)	PUMA	Northern part of the Dutch Randstad, The Netherlands	farmer, authority, investor, developer, household, firm	yes	yes	no
Fontaine and Rounsevell (2009)	HI-LIFE	East Anglia, UK	households	no	yes	no
Jjumba and Dragićević (2011)	Agent iCity	City of Chilliwack, Canada	planner, developer, household, retailers, industrialists	no	yes	no
Kii and Doi (2005)	MALUT	Takamatsu city, Japan	household, firms	yes	yes	energy consumption
Miller et al (2008); Salvini and Miller (2005)	ILUTE	Greater Toronto Area, Canada	developer, household, firm	yes	yes	energy consumption, greenhouse gas emission, air quality
Waddell (2002); Waddell et al (2003, 2008)	UrbanSim	Eugene-Springfield, Oregon, USA	household, business, developer, government	yes	yes	no
Wagner and Wegener (2007)	ILUMASS	Metropolitan area of Dortmund, Germany	household, business, developer	yes	yes	air quality, traffic noise
Wu and Birkin (2012)	MoSeS	Leeds, UK	household	no	yes	no

a developer, location choice of firms and businesses, and policy and planning proposed by government and planning authorities (table 3).

- Life-cycle events and daily activities (eg, travel routines to work or shopping) play an important role in influencing residential choice in these models. Members of a large population of heterogeneous individuals will make a residential choice according to their sociodemographic attributes, such as age, marital status, children, job location, and shopping patterns. Agent-based modeling is fused into MSM, thereby contributing the ability to simulate the social behavior of individuals, such as preferences, risk attitudes, and plans (Birkin and Wu, 2012).
- Another feature of these models is that they are highly related to policy and planning analysis. Thus, the population dynamics, travel patterns, and consequences of urban land-use change are simulated according to various what-if scenarios. All these models have evaluated policy-related scenarios, and more than half of them incorporate traffic patterns (5/8, see table 3). In addition, environmental consequences of energy consumption (Chingcuanco and Miller, 2012; Kii and Doi, 2005), air pollution (eg, greenhouse gas emission, air quality, population exposure), and noise (Hatzopoulou et al, 2011; Wagner and Wegener, 2007) are assessed.

- These models are designed and applied mainly in developed countries. Despite the benefits of economies of scale, urbanization brings in socioeconomic and environmental costs in developed and developing countries. However, MSM requires abundant data consisting of census tables, housing surveys, remotely sensed images, and traffic records. These data are rarely recorded or available in developing countries at the extent required by MSMs.
- All these models belong to long-term ongoing projects. For instance, the ILUTE model was developed by a group of researchers led by Miller at the University of Toronto and was first presented in 1998 (Miller et al, 2008; Salvini and Miller, 2005). After its initial framework, continuing efforts have been made to synthesize the population data (Pritchard and Miller, 2012), improve the performance and the authenticity of the model [eg, a new module simulating disequilibrium dwelling space under different market conditions (Farooq and Miller, 2012)], and validate the results (Miller et al, 2011). Other projects follow similar long-term improving development.

It is clear that some models cover more than one domain (see the second column in table 4: the research domain). It is also evident that some long-term projects tend to develop from a purely theoretical stylized model to a more realistic model driven by empirical data (ie, the space is still highly abstract but parameterization is driven by empirical data) and then to a fully empirical model (see the third column in table 4).

3 Urban residential choice model based on agent-based modeling

One of the essential differences between an ABM and previous models (eg, system dynamics, cellular automata) is the farmer's ability to simulate emergent patterns from the decision-making processes and behaviors of individual intelligent agents. This ability grants modelers more freedom to explicitly model causal factors and agents' behaviors, and to represent model output. This review of ABMs further focuses on the three features: AH, LMR, and OM.

3.1 Agent heterogeneity

AH is one of the main reasons that agent-based modeling is attractive to researchers in simulating residential choice in an urban context. The limitations and restrictions of a single representative agent and the requirement for static equilibrium conditions faced by traditional economic models can be relaxed to include AH (Arthur, 1999; 2005; Axtell, 2000; 2003; Epstein, 1999; Farmer and Foley, 2009; Hommes, 2005; Tesfatsion, 2006). While some analytical urban models incorporate AH, they do it only within a 1D landscape, which can be heterogeneous in a maximum of two attributes, because the difficulty in finding an analytical solution increases prominently as an additional source of AH is incorporated (ie, an additional heterogeneous agent attribute) (Anas, 1990; Epple and Platt, 1998; Irwin, 2010). Moreover, a greater variety of emergent landscape patterns and LUCC (land-use and land-cover change) phenomena can be simulated from the bottom up: for example, urban sprawl, urban gentrification, and residential segregation (table 4).

3.1.1 *Ways to model agents' heterogeneity*

From a broad perspective, heterogeneity among agents in an ABM can be introduced through multiple types of agent. The interactions between different types of agent may also lead to different model outputs. In this review, however, we define AH more narrowly. Specifically, AH refers to differences in attributes and decision-making rules among individuals within the same agent type. The differences could be either internal (eg, demographic and household characteristics, personal experiences, expectations, and risk attitudes) or external (eg, social networks, accessibility to information, and policies) (Irwin, 2010; Valbuena et al, 2008).

Table 4. Market representation and agent heterogeneity in existing agent-based urban residential choice models. (See below for definitions of code letters.)

Model name/main developers	Domain	Data	Agents	Resources constraints	Competitive bidding	Endogenous relocation	Measures of performance	Number of heterogeneous agent attributes	Effect of agent heterogeneity
OBEUS/Benenson (Benenson, 1998; 1999; Benenson et al, 2002; 2005; Omer, 2005)	Se	both	R	yes	no	yes	SD+SI	>3	yes
MASUS (Feitosa et al, 2011)	Se	empirical	H	yes	no	na	SD+SI	>3	yes
Simseg (Fossett, 2006a; 2006b; Fossett and Dietrich, 2009; Fossett and Waren, 2005)	Se	both	H	yes	yes	yes	SD+SI	2	no
O'Sullivan (O'Sullivan et al, 2003)	Se	artificial	R	no	no	yes	SD+SI	1	no
Laurie and Jaggi (Laurie and Jaggi, 2003)	Se	artificial	R	no	no	yes	SD+SI	2	no
Yin (Yin, 2009)	Se	empirical	R	yes	no	yes	SD+SI	2	no
Wasserman and Yohe (Wasserman and Yohe, 2001)	Se	artificial	R	no	no	yes	SD+SI+AM	2	no
Xie (Xie and Zhou, 2012)	Se	semi- empirical	R	no	no	yes	SI	1	yes
Bruch (Bruch and Mare, 2006; 2009)	Se	artificial	R	no	no	yes	SI	1	yes
Benenson (Benenson and Hatna, 2011; Hatna and Benenson, 2012)	Se	artificial	R	no	no	yes	SD+SI	1	no
Gilbert (Gilbert et al, 2009)	Se	semi- empirical	R+A	yes	no	yes	SD+SM+AM	1	no
Ellis (Ellis et al, 2011)	Se	artificial	R	no	no	yes	SI	1	no
Crooks (Crooks, 2006; 2008)	Se/Mo	artificial	R/R+B	na	na	na	SD+SI	2	no
Jayaprakash (Jayaprakash et al, 2009)	Se+Ur	artificial	R	yes	no	yes	SD+SI	3	no
Jordan (Jordan et al, 2012)	Se+Ur	empirical	R	yes	no	yes	SD+LM	>3	no

Table 4 (continued).

Model name/main developers	Domain	Data	Agents	Resources constraints	Competitive bidding	Endogenous relocation	Measures of performance	Number of heterogeneous agent attributes	Effect of agent heterogeneity
ALMA (ALMA-C) (Filatova et al, 2009a; Parker and Filatova, 2008)	Mo	artificial	R+F	yes	yes	no	SD+LM+SM	1	yes
CHALMS (Magliocca et al, 2011)	Mo	empirical	H+D+F	yes	yes	no	LM+SM	2	no
Chen (Chen et al, 2011)	Mo	semi-empirical[a]	H+F+A	yes	yes	no	SD+AM+SM	2	yes
SOME (Brown et al, 2004; 2005; Brown and Robinson, 2006; Zellner et al, 2010)	Ur	both	R	no	no	no	SD+LM+AM	1	yes
SOME+DEED (Brown et al, 2008)	Ur	empirical	R+B+F+G	no	no	no	na	1	no
Caruso (Caruso et al, 2005; 2007; 2009)	Ur	both	R+F	yes	yes	yes	SD+LM+SM	0	no
Diappi (Diappi and Bolchi, 2008)	Ur	artificial	R+D+T+L	yes	na	yes	SD	2	no
Ligmann-Zielinska (Ligmann-Zielinska, 2009; Ligmann-Zielinska and Sun, 2010)	Ur	artificial	D	no	yes	no	SD+LM	2	yes
Jackson (Jackson et al, 2008)	Ur	empirical	R	yes	na	yes	SD	>3	no
Torrens (Torrens, 2007)	Ur	artificial	R	yes	no	yes	SD	>3	no
Xie (Xie et al, 2007)	Ur	empirical	D+B	no	no	no	SD+SM	1	no
O'Sullivan (O'Sullivan, 2002)	Ur	empirical	R+T+L	yes	no	yes	na	2	no
STAU-Wien (Loibl et al, 2007; Loibl and Toetzer, 2003)	Ur	empirical	H+B	no	no	no	SD	>3	no
ABLOoM (Otter et al, 2001)	Ur	artificial	H+B	yes	no	no	SD	>3	no
Sasaki (Sasaki and Box, 2003)	Ur	artificial	F	yes	no	yes	SD+LM	2	no
Li (Li and Liu, 2007)	Ur	empirical	H+D+G	yes	no	yes	SD	3	no
Tao and Li (Tao et al, 2009)	Ur	empirical	H	yes	na	yes	SD+SM	2	no

Table 4 (continued).

Model name/main developers	Domain	Data	Agents	Resources constraints	Competitive bidding	Endogenous relocation	Measures of performance	Number of heterogeneous agent attributes	Effect of agent heterogeneity
Yin and Muller (Yin and Muller, 2007)	Ur	empirical	H	no	no	no	SD+LM	1	no
Augustijn-Beckers (Augustijn-Beckers et al, 2011)	Ur	empirical	R+T	yes	no	no	SD+LM	3	no
RESMOBcity (Haase et al, 2010)	Ur	empirical	H	no	no	no	SD+AM	>3	no
Barros (Barros, 2012)	Ur	empirical	R	yes	yes	yes	SD+ SI	1	no
Tian (Tian et al, 2011)	Ur	empirical	G+D+H+E	no	no	no	SD+LM	1	no
SLUCEII-ABM (Parker et al, 2012b; Robinson et al, 2010)	Ur+Mo	empirical	R+F+D+A	yes	yes	yes	SD+LM+EM	>3	no
MOLA + ABM (Ligmann-Zielinska and Jankowski, 2010)	Ur+PI	empirical	D	no	no	no	SD+LM	1	no
Robinson (Robinson et al, 2012)	Ur+PI	empirical	R+D	no	no	no	SD+EM	>3	no
Monticino (Monticino et al, 2007)	Ur+PI	empirical	F+D+G+R	yes	no	no	SM	3	no
AusUrbia (Heckbert and Smajgl, 2005)	Ur+PI	empirical	F+R+D	yes	yes	yes	SD+SM+AM	>3	no
Ligtenberg (Ligtenberg et al, 2004)	Ur+Pl	empirical	H+P	no	no	no	SD+LM	2	no
Jjumba (Jjumba and Dragićević, 2011)	Ur+Pl	empirical	P+D+H+B	yes	no	yes	SD+LM	2	no
PUMA (Ettema et al, 2007)	MS	empirical	B+H+F+G+D	yes	na	na	SD	>3	no
ILUMASS (Wagner and Wegener, 2007)	MS	empirical	B+D	yes	na	yes	SD	>3	no
UrbanSim (Waddell, 2002; Waddell et al, 2003; 2008)	MS	empirical	G+H+B+D	yes	na	yes	na	>3	no

Table 4 (continued).

Model name/main developers	Domain	Data	Agents	Resources constraints	Competitive bidding	Endogenous relocation	Measures of performance	Number of heterogeneous agent attributes	Effect of agent heterogeneity
ILUTE (Miller et al, 2008; Salvini and Miller, 2005)	MS	empirical	D+H+B	yes	yes	yes	na	>3	no
MALUT (Kii and Doi, 2005)	MS	empirical	H+B	yes	yes	yes	SD+EM	3	no
MoSeS (Wu and Birkin, 2012; Wu et al, 2008)	MS	empirical	R+T	no	no	no	SD+LM	>3	yes
HI-LIFE (Fontaine and Rounsevell, 2009)	MS	empirical	H	yes	no	yes	SD+AM	>3	no

Abbreviations
Domains. Se: segregation; Mo: monocentric city and its variation; Ur: urbanization stage; Pl: planning; MS: microsimulation
Agents: R: residents; F: farmers (landowners); D: developers; G: government; H: households; T: tenant; L: landlord; B: business (firms); P: planner; E: environmentalist; A: auctioneer (broker, or real estate agent)
Performances. SD: spatial distribution of land use; LM: landscape metrics; SM: socioeconomic metrics; AM: agent-level metrics; SI: segregation index; EM: environmental measures
[a] Only the parameters are derived from empirical data, the space is artificial.

Table 5. Matrix classification of agent heterogeneity.

Decision-making rules	Attributes	
	constant	variable
Constant	I	III
Variable	II	IV

The method to incorporate AH into an urban ABM depends on the objective of the study and data availability in an empirical case study (Smajgl et al, 2011). On the basis of the division between categorization and variation proposed by Brown and Robinson (2006), approaches to introduce AH are divided and categorized in a matrix though the representation of attributes and decision-making rules (table 5).

Category I. During an entire model run the attributes and decision-making rules of agents remain constant. Agents are usually identical within the same agent type. Typical examples can be found in the variations of the Schelling's segregation models. In most cases, agents maintain their attributes (ie, threshold to move) and decision-making rule (ie, tolerance of neighborhood composition) throughout (Benenson and Torrens, 2004b; Schelling, 1971). Examples can be also found in various empirical models (Diappi and Bolchi, 2008; Kii and Doi, 2005; Tian et al, 2011; Torrens and Nara, 2007).

Category II. The second approach is to divide the agents into different groups within an agent type. In this category, agents' attributes are still invariant during a model run, but their decision-making rules are differentiated. For example, in the segregation model adopted by Jayaprakash et al (2009), black residents are indifferent to the composition of their neighborhood while the white residents are averse to living in a black neighborhood. Another example can be found in the research conducted by Fernandez et al (2005). They implemented cluster analysis to classify the exurban households into different groups according to their socioeconomic and demographic characteristics. These groups have different preferences (ie, weights) for residential choices (see also Brown and Robinson, 2006).

Category III. In contrast to the former two categories, agents' attributes are no longer invariant in the third (and fourth) category of ABMs. Their attributes can change with the evolution of time and interaction with other agents and the environment. Agents in model integrated with MSM usually belong to these two categories as life-cycle events, such as marriage, birth of a child, or divorce, that will greatly impact households' decision on the location and preference for a house (eg, house type, number of rooms, and number of bathrooms). In category III, agents follow a constant decision-making function even if some input components are temporally dynamic (eg, age, number of persons, total income). For example, Barros (2003; 2012) simulated peripherization in Latin America. In their model, the decision-making rule (ie, the property is acquired by an agent who is more economically powerful than other bidders) is constant while their attribute, individual income, can vary over time.

Category IV. Both the agents' attributes and their decision-making rules vary in the fourth category. In this category, some of agents' attributes will change over time, and when they reach certain conditions, agents will adapt another decision-making rule. For instance, an empirical ABM–MSM is used to simulate the spatial location of student populations in Leeds (Wu and Birkin, 2012; Wu et al, 2008). Four types of student (ie, first-year undergraduates, second-year or third-year undergraduates, master students, and PhD students) and their differences in housing priorities are identified by census data and household surveys. More specifically, first-year undergraduates tend to stay in university accommodation, and second-year or third-year undergraduates often prefer private rented accommodation. Each agent will experience an aging process and change their rules accordingly.

3.1.2 *Evaluating the effect of agent heterogeneity*

Currently, the most common method from evaluating the effect of AH on the output of ABMs is to compare the results between a baseline scenario with homogeneous agents or agents with random attributes and a scenario with heterogeneous agents. The comparison usually supports the importance of AH and demonstrates biases when AH is omitted. For example, Filatova et al (2011a) find qualitatively different results in spatial and economic metrics in hazard-prone areas (leading to very different policies to be applied) between households with heterogeneous risk perceptions based on the empirical survey distribution and homogeneous agents with risk perception equal to the average of the population.

In addition to that simple comparison, the effect of AH has been further evaluated by varying the distributions of agents' attributes. Using an exurban development model, SOME, Brown et al (2006) introduce AH derived from survey results in five different distributions by varying overall/group means and standard deviations of agents' attributes. The result of sensitivity analysis confirms that adding AH can significantly influence the spatial pattern of sprawl and clustering development. Researchers also vary the level of AH and assess its impact on the results. For instance, Chen et al (2011) found heterogeneity in income can lead to leapfrog development in an exurban area and that exurban development is encouraged when the level of income heterogeneity is more severe.

Although heterogeneous agents are adopted in numerous models and the effects of AH are emphasized by researchers, comprehensive methods designed to evaluate and understand the effect of AH in a systematic way are rare. Less than 20% of these models (9/51) have evaluated the effects of AH, although all of them represent AH to some extent (table 4). The deficiency in methods for evaluating the effects of AH is magnified when there are multiple sources of AH (ie, multiple heterogeneous attributes of an agent and/or heterogeneous decision-making processes). Nearly 71% of models (36/51) have agents with more than one source of AH (ie, a single heterogeneous agent attribute), but none of them evaluate the effect on outcomes by sequentially adding new sources of AH or increasingly magnifying the degree of heterogeneity (table 4).

In summary, AH is a double-edged sword. It is one of the driving forces for residential decision in an urban context. It also introduces additional uncertainties and difficulties in verification and validation of ABMs (Evans, 2012; Manson et al, 2012; Miller et al, 2011). How to incorporate AH appropriately is an important question, which affects the performance of any model. To respond to this challenge, an ABM developer should critically reflect on the number of dimensions of attributes' heterogeneity, on the level of AH, and on the interaction among different heterogeneous agents.

3.2 Land-market representation

A number of researchers have emphasized that the land market should be represented in spatially explicit urban land-use models to better explore and simulate the complex interactions between economic and natural systems (Haase and Schwarz, 2009; Irwin, 2010; Irwin and Geoghegan, 2001; Ligmann-Zielinska and Jankowski, 2007; Parker and Filatova, 2008). As Parker and her colleagues (2012a) argue, land-market factors, ranging from credit availability, interest rates, the strength of demand relative to supply, and institutional details of the land market to subsidies, taxes, quotas and insurance, will affect land-use change spatially and quantitatively. Applications of ABMs with land-market representations are increasing, and a detailed review is given below.

3.2.1 *Representations of market processes in practice*

To study the impacts of LMR, Parker et al (2012a) identify five market levels ranging from a simple form to a complex structure. As the market level increases, a new land-market element is progressively added: locational preferences, resources constraints, competitive bidding, strategic behavior, and endogenous supply decisions. The first three market elements are commonly found in existing spatially explicit ABMs. In addition, endogenous relocation is frequently modeled, even in the absence of LMR. However, the real relocation processes, the timing and motivation of relocation, are highly related to economic conditions, such as moving cost, employment opportunity, income increase, and neighborhood quality (Parker et al, 2012a). Therefore, we regard endogenous relocation as a land-market element and compare the differences in representing these four elements across the fifty-one models (table 4).

- *Preferences*: residential choice is made according to a utility-measuring or suitability-measuring function. Agents have heterogeneous preferences for properties according to the location, the neighborhood of the property, and their socioeconomic characteristics. Almost all the models (table 4) have functions evaluating the attractiveness of property. Although the final residential choice is based on utility, the methods of calculating utility vary. The Cobb–Douglas function is the most commonly used functional form in urban economics due to its analytical tractability (Wu and Plantinga, 2003). The preference coefficient in the Cobb-Douglas utility function represents not only the strength of attractiveness of a certain locational attribute but also a share of the budget an agent is willing to pay for it. Examples can be found in the models of SOME (Brown and Robinson, 2006), the ALMA series (Filatova et al, 2009a), CHALMS (Magliocca et al, 2011), and HI-LIFE (Fontaine and Rounsevell, 2009). Other methods are also adopted by researchers, such as the ideal point decision rule implemented by Ligmann-Zielinska (2009), where the utility is determined by the attractive differences between a given property, the ideal property, and the nadir property. Another example is the heuristic approach used by Jackson et al (2008). In this model, four types of agent choose their properties by different criteria in a decision-tree fashion.
- *Resource constraints*: resource constraints mean that buyers' residential choices are restricted by their budgets. In other words, resource constraints reflect the affordability of housing for buyers. Commonly, a buyer agent provides a valuation (WTP) and/or a bid price for a specific parcel, and this depends on their fixed housing budgets. There are also cases in which their residential choices are indirectly determined by the average income conditions in the neighborhood (Benenson, 1999; Tao et al, 2009). Among all the fifty-one models, nearly two thirds (31, or 61%) have the component of resource constraints (see table 4). For example, heterogeneous incomes work as a constraint on renting or buying a house in a gentrification model (Jackson et al, 2008; O'Sullivan, 2002), and a driving force causing segregation patterns in residency (Feitosa et al, 2011; Jayaprakash et al, 2009).
- *Competitive bidding*: the sequence of parcel allocation is determined via a competitive bidding process, in which only the buyer providing the highest WTP acquires the parcel. Only eleven models have the competitive bidding process, while thirty-one models lack it. (Some models did not describe their parcel allocation method in the publications.) The bidding process allocates properties among agents not only in space but also in time (Chen et al, 2011). It is explicitly defined as a competitive market in which agents make a bid for locations that maximize their utility (Parker and Filatova, 2008). Sometimes it is simulated in an indirect way: for example, as a negotiation process (Ettema, 2011) or an accumulating application process (Li and Liu, 2007).

- *Relocation* is the process by which residents who have settled earlier decide to move to another location. In a broad perspective, not only migrating residents who remain in the model, but also residents who leave the system are regarded as relocated agents. It is simulated in thirty (about 59%) of the reviewed models (table 4), although some of them do not model it as an endogenous process and do not involve interactions between relocation and market elements. For instance, in the ABM simulating a gentrification process, agents are forced to relocate by economic imperative, namely, when they cannot afford their current places (Jackson et al, 2008), while in most variations of the Schelling's segregation models, agents' movements are driven by increasing dissimilarity of ethnic composition at the local neighborhood level (Benenson and Torrens, 2004a).

3.2.2 *Open questions in ABMs with land-market representation*

Our review reveals that some complex land-market elements, such as competitive bidding, are incorporated less frequently in models (see table 4). The objective of any model is, on the one hand, to replicate the real situation as precisely as possible, and on the other hand, to keep the model as simple as possible. The tradeoff between the simplicity of the model and the robustness of results gives rise to the open question: do the effects of diverse land-market elements contribute to improving the validity and robustness of the model? Meanwhile, researchers argue that different elements of market representation could significantly influence both the complexity of a model and its spatial and economic outcomes (Polhill et al, 2007). However, to our knowledge, there is no research systematically investigating how all these market elements affect the spatial and economic patterns and trajectories of land-use change. Here the open question is: how can the effects of diverse land-market elements in the design of an ABM and concomitant experiments be evaluated? A potential approach to this challenge is illustrated by Huang et al (2013).

Additionally, as more land-market elements are simulated in the model, the implications of a much broader range of policies, especially economic policies, can be tested in the model, and this will potentially provide insightful information to support decision making of planners and stakeholders. The open question here is: how can the transparency of land-market processes as well as the reliability of output to their decisions be ensured?

3.3 Measurement of outcomes

Relative to simpler modeling methods, agent-based modeling brings another dimension of outcomes because it can simulate the decisions and behaviors of individual agents and consequent emergent patterns. Meanwhile, random processes are incorporated in the simulation of agents. Collectively, these dimensions increase the challenge for measuring model outcomes.

3.3.1 *Landscape-level and aggregated-level outcomes*

Traditionally, urban land-use models provide spatial outcomes of land-use composition and pattern, and socioeconomic outcome at a landscape or an aggregated level. These outcomes are further analyzed to validate the model and provide projections under what-if scenarios. Spatial metrics, which stem from landscape ecology in the late 1980s and are based on a categorical, patch-based representation of a landscape, are the most common method for analyzing spatial patterns (Herold et al, 2005). About 85% of the models (43/51) use spatial distributions or landscape metrics to analyze their results: for example, the measure of fragmentation and land-use diversity caused by externalities in urban ABMs (Brown et al, 2004; Parker and Meretsky, 2004), or the measure of segregation by income or cultural/ethnical identity (Benenson, 1998; Fossett and Waren, 2005; Jayaprakash et al, 2009; Omer, 2005; Schelling, 1971).

3.3.2 *Individual-level outcomes*
At the same time, due to AH and LMR, urban residential choice ABMs provide process-based results and socioeconomic outputs at the individual level, such as individual transaction prices, social welfare, and bidding history. This additional information also has the potential to play an important role in model verification, validation, and result analysis (Evans, 2012; Ngo and See, 2012). It also has the ability to enrich our understanding of the complex processes of LUCC and their consequences. For instance, the detailed trajectories of LUCC at the agent level can be used to explore the path-dependent process of residential choice. However, only seven models (14%) use individual information in their analysis, and only nine (18%) use economic results to validate a model's performances. Examples include the rent map and curve used by Caruso et al (2005; 2007; 2009) and the regression analysis used by Xie et al (2007). Therefore, how to analyze the broad dimensions of outcomes at the agent level is a challenge yet to be overcome.

3.3.3 *Stochasticity and repetitive runs*
Incorporation of intelligent adaptive agents in a model adds more random and stochastic factors and processes. Therefore measurement of output based on a single run of a model under a given parameter setting would not be representative. Repetitive model runs are required to ensure that an outcome is stable irrespective of a random seed. Modelers use different approaches to retrieve information from repetitive runs. The most straightforward method is to use the averages and variances of outputs after repetitive runs (Brown and Robinson, 2006; Crooks, 2010; Ettema, 2011; Magliocca et al, 2011; O'Sullivan et al, 2003; Zellner et al, 2010). Another common method is to conduct a formal sensitivity analysis (Caruso et al, 2007; Jackson et al, 2008; Kii and Doi, 2005; Ligmann-Zielinska and Jankowski, 2010; Ligmann-Zielinska and Sun, 2010; Loibl and Toetzer, 2003; Loibl et al, 2007). Statistical tests, such as the *t*-test (Filatova et al, 2009a; 2009b; Wasserman and Yohe, 2001) and ANOVA analysis (Sasaki and Box, 2003), are also conducted to confirm the stability of outcomes. However, there is no agreement on either the criteria determining the number of repetitive runs or a method of analyzing the outcomes of repetitive runs.

4 Discussion and conclusions
In this paper we have provided an overview of functionalities brought by agent-based modeling to simulate urban residential choices, with specific attention to AH, LMR, and measurement of outcomes. Following the continuum from theoretical to empirical, the fifty-one models reviewed in this paper can be generally divided into three categories: classical models extended using agent-based modeling, models simulating different stages of the urbanization process, and integrated agent-based modeling and MSM. Their features are summarized and compared within each category of models.

Three distinctive features stemming from the agent-based modeling technique are reviewed and discussed in detail. The first is AH, which is introduced into a model by changing either agents' attributes or their decision-making rules. However, the insufficiency of methods to evaluate the effects of AH on the outcomes of urban dynamics and patterns might be a challenge in guaranteeing the validity of simulation results. The second feature is the level of LMR, which can be gradually increased by adding resource constraints, competitive bidding, and endogenous relocation upon a residential choice driven by preferences only. Among the four elements reviewed here, preferences are the most commonly represented element, while competitive bidding is the least used. Resource constraints and endogenous relocation are less popular than preferences, and the implementation of endogenous relocation usually does not represent the direct interaction between household and land market. The necessity for and methods of assessing the effects of diverse LMR will be a priority area of study when incorporating land market elements in an ABM. And the last feature is methods to analyze macrolevel and microlevel outcomes of an ABM. Traditional measurements, such as spatial metrics alone, are insufficient to study an ABM outcome. It is necessary to use a wider range of methods, metrics including individual-level observations to study and visualize outputs, and to verify and validate models.

Urban land-use models can benefit from agent-based modeling by incorporating heterogeneous intelligent agents and explicit modeling of an institution that stands behind land exchange (ie, LMR in this case). However, the flexibility of the modeling technique and the consequent broader dimension of outcomes will also bring considerable challenges. First, the trade-off between the simplicity of the model and the ability to replicate complex human–environment interactions in the urban context provide a great challenge for researchers. A model is an abstract simplification and representation of the real world rather than a complete replication of reality (Chorley and Haggett, 1967). Thus, the important question is whether these features (eg, AH and LMR) brought by ABMs are essential and necessary for simulating urban residential phenomena (O'Sullivan et al, 2012). In other words, the decision to include AH or land-market elements depends on their likely influence on urban residential patterns, and whether the final results will be significantly biased or conflicting if they are excluded.

Second, when more features are simulated in the model, representing the interactions within each feature and between features poses another challenge. As discussed in subsection 3.1, AH suggests agents may vary in multiple attributes and their decision-making rules. The interaction within multiple numbers of heterogeneous agent attributes, and between AH and LMR, is complex and nonlinear, which can potentially lead to unexplored effects. The exploration of nonlinearity, complexity, and sensitivity, therefore, need to be conducted beforehand to confirm the reliability of a model (Parker et al, 2002).

The third challenge is the conflict between the demand for data at the individual level and the scarcity of available data (Batty et al, 2012). AH raises a strong demand for data at the individual or household level, which are relatively rare in historical records and censuses. Sometimes its representation requires conducting extensive surveys, role-playing games, or laboratory experiments to collect behavioral data. The uncertainty within the data and the inconsistency between observed patterns and stated preferences in surveys are further obstacles in simulation (Evans, 2012). Moreover, since ABMs generate output data at both the macrolevel (eg, aggregated spatial patterns and socioeconomic measures) and the microlevel (eg, changes in individual welfare and evolution of individual decisions rules or opinions) across multiple dimensions (e.g., spatial, economic, demographic), new methods of measuring, visualizing and communicating these outputs are greatly needed (Grimm and Railsback, 2012; Parker et al, 2003).

Acknowledgements. This work is supported by the US National Science Foundation's Coupled Natural and Human Systems Program "SLUCE II project (Spatial Land Use Change and Ecological Effects) NSF CNH-0813799, the scholarship provided by the Chinese Council, the State Key Laboratory of Earth Surface Processes and Resource Ecology of Beijing Normal University (No. 2013-RC-03), and the Netherlands Organization for Scientific Research (NWO) VENI grant 451-11-033. The authors also thank Jonathan Li, Peter Deadman, Derek Robinson, Eric Miller, the anonymous reviewers, and the editor for their valuable comments and suggestions.

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