Market Impacts on Land-Use Change: An Agent-Based Experiment

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MarketImpacts on Land-Use Change: An Agent-Based Experiment

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Land-use change in a market economy, particularly at the urban–rural fringe in North America, is shaped through land and housing markets. Although market activities are at the core of economic studies of land-use change, many market elements are neglected by coupled human–environment models. We scrutinized the effects of the level of detail of market representation using an abstract, agent-based model of land-use change. This model includes agents representing land buyers and sellers and their respective market-based decision-making behaviors. Our results show that although incorporating key market elements, particularly budget constraints and competitive bidding, in land-use models generally alters projected land-use patterns, their impacts differ significantly depending on the level of detail of market representation. Consistent with theories of land change, our research confirms that budget constraints can considerably reduce the projected quantity of land-use change. The effects of competitive bidding, however, are more complex and depend on buyers’ budgets, their relative preferences for proximity versus open-space amenities, and the size of neighborhoods. Market competition might reduce or increase the quantity of land-use change and the degree of sprawl in the simulated landscapes. Because of the strong effects of market elements on resulting patterns, adequate representation of the structure of markets is important for capturing and characterizing the complexity inherent in coupled human–environment systems.

Key Words: agent-based modeling, land markets, land-use change.

市场中的土地使用变迁，特别是在北美城乡交界边缘处，是透过土地与住房市场形塑而成。尽管市场活动位于土地使用变迁经济研究的核心，诸多市场元素却被人类—环境的结合模型所忽略。我们运用以行动者为基础的土地使用变迁模型，探究市场再现的细节程度之影响。此一模型包含代表土地购买者与出售者的行动者，及其各自以市场为基础的决策行为。我们的研究显示，尽管将主要的市场元素纳入土地使用模型，特别是预算限制与竞争性投标，一般而言改变了推断的土地使用模式，但它们的影响，却根据市场再现的细节程度而显着不同。我们的研究与土地变迁理论一致，证实了预算限制会大幅减少推测的土地使用变迁。但竞争性投标的影响却更为复杂，取决于买家的预算、他们在邻近性之上开放空间环境之间的相对偏好，以及邻里的规模。在模拟的案例中，市场竞争或许会减少或增加土地使用变迁量及蔓延的程度。因为市场因素对于模式后果的强大影响，市场结构的适宜再现，对于捕捉并描绘人类—自然结合的系统的内在复杂性而言相当重要。 关键词: 以行动者为基础的模式化，土地市场，土地使用变迁

El cambio de uso del suelo en una economía de mercado, particularmente en la orla urbano-rural de Norteamérica, es determinado por los mercados de la tierra y la vivienda. Aunque las actividades económicas son mediadoras en los estudios económicos sobre cambio del uso del suelo, muchos de los elementos del mercado suelen desecharse en los modelos que expresan la relación humano-ambiental. Escudriñamos los efectos que tiene el nivel de detalle de la representación mercantil utilizando un modelo abstracto de uso del suelo basado en agente. Este modelo incorpora agentes que representan compradores y vendedores de terrenos y sus respectivos comportamientos de toma de decisiones con base en el mercado. Nuestros resultados muestran que aunque incorporan elementos claves del mercado, en particular restricciones presupuestales y puja competitiva, en el uso de la tierra los modelos generalmente alteran los patrones de uso del suelo proyectados, y sus impactos difieren significativamente dependiendo del nivel de detalle en la representación del mercado. Consistente con las teorías sobre cambio de

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Land-use change (LUC) is one important point of interaction between human and environment systems. In market-based economies (e.g., North America), LUC is largely shaped by the buyers and sellers of land via their land and housing markets decisions (Lambin et al. 2001; Verburg et al. 2004). Despite their fundamental role, land markets are neither conceptualized nor implemented well in many spatially explicit LUC models (Irwin and Geoghegan 2001; Irwin 2010). Most existing demand-driven agent-based models (ABMs) of LUC can successfully replicate macro spatial patterns of real-world land change (e.g., Brown et al. 2004; Manson 2005, 2006; Brown and Robinson 2006). Without market mechanisms, however, few of them can incorporate or produce market-based policy recommendations such as environmental impact fees, subsidies for ecological services, or tradable pollution permits (Lubowski, Plantinga, and Stavins 2006; Nelson et al. 2008; Filatova, Voinov, and van der Veen 2011). More critically, even though some models include market elements such as utility maximization and budget constraints, to our knowledge, few formal comparisons have been conducted to explore whether and how the representation of land markets significantly affects projected outcomes of these spatial LUC models.

The value of examining the role of markets in LUC models is twofold. First, land and housing markets have been shown to be dominant drivers of LUC and act as conduits for many changing socioeconomic contexts such as credit availability, interest rates, and population growth (Randall and Castle 1985; Grevers 2007; Lubowski, Plantinga, and Stavins 2008). It is therefore necessary to understand their influence on the rate and extent of LUC in a study area. Second, market structures that affect the interactions among landowners, developers, buyers, and environmental policies intervene in those interactions through market instruments (e.g., cap-and-trade programs that create markets for land-related services), alter socioeconomic dynamics, and subsequently affect LUC and environmental processes. By explicitly modeling the land market we can gain a better understanding of how LUC decisions are made and how they are influenced by policies (Parker et al. 2003; Manson and O’Sullivan 2006; Manson 2007; Parker and Filatova 2008).

To test the effects of markets on the outcomes of LUC models, we present experimental results from an ABM of LUC, Land Use in an eXurban Environment (LUXE), that is designed with multiple levels of market representation. Spatially explicit ABMs of LUC at the urban–rural fringe in North America have made increasingly important contributions to research on exurban LUC because of their ability to model complexities integral to human–environment interactions (Parker et al. 2003; Brown et al. 2008; Irwin 2010). LUXE is designed to generalize, at a simplified level, across a large number of such models. The experiments aim to address the question of whether and how details of market interactions alter the outcomes of LUC models.

The rest of the article is structured such that the next section reviews the state of the art in representing land markets in agent-based LUC models. The design and implementation of multiple elements of land markets in LUXE are described after that. We then present the analysis and interpretation of model results using descriptive statistics, linear regression, and visualization. The article concludes with a discussion of the importance of representing different elements of the land market in LUC, their effects on model outputs, and future research directions.

Land Markets and Land-Use Change

We define a land market (LM) as a collection of land exchanges between buyers and sellers of land within a bounded region that sets land prices. Consistent with theoretical urban economics (Alonso 1964; Randall and Castle 1985; Wu 2010), the shape and size of land parcels in our model are homogeneous. Variation of land prices arises from different locational characteristics; that is, open-space amenities in the local neighborhood and proximity to the urban center, as well as heterogeneity of preferences and budgets of economic agents trading those parcels.
**Land Markets in Geography and Economics**

Land markets are geographically localized, segmented, and heterogeneous (Goodman and Thibodeau 2003; Helbich et al. 2013). The quality and desirability of a land parcel are determined both by site characteristics and by locational amenities. They are also defined by and expressed as neighborhoods, delineated by fuzzy boundaries derived from the built environment, natural features, functional relationships, population migration, and administrative units (Adams 1984; Cheshire and Sheppard 1995; DiPasquale and Wheaton 1996; Sun and Manson 2012). The price of a residential land parcel, for example, is affected not only by its suitability for housing construction but also by local neighborhood quality and accessibility to various social and ecological services. Conversely, land markets also partially define neighborhoods. Market-driven LUC and residential land development generate socioeconomic externalities within and across spatial neighborhoods, which affect amenities of nearby locations (Irwin and Bockstael 2002; Plantinga, Lubowski, and Stavins 2002). Such internal feedbacks, spatial externalities, and sensitivity to external conditions characterize the complex nature of LM and LUC (Parker et al. 2003; Manson and O'Sullivan 2006; Irwin 2010).

LM processes have been captured to various extents by two streams of research. First, analytical LM models demonstrate how the land price endogenously forms through the interaction of market forces using mathematical means like partial differential equations. Although these models have become considerably comprehensive (e.g., Wu 2010), the number of locational characteristics and the level of agent rationality and heterogeneity are rather limited. Second, spatial econometric models, accounting for a rich variety of spatial characteristics, can more effectively capture the outcome of LM forces. They typically provide only one or a few snapshots of the market, however, and do not account for agent heterogeneity (Bockstael 1996). ABMs combine spatial heterogeneity and dynamic decisions of heterogeneous agents in LMs and can help address these issues (Parker et al. 2003; Brown and Robinson 2006).

**Land Markets in LUC Models**

We reviewed thirty-one micro-LUC models published in academic journals that include at least a land utility maximization algorithm or variations like highest suitability (Table 1), with additional details and analysis provided in Huang et al. (forthcoming). We particularly examined how these models implement LMs and endogenously form land prices. From the analysis, we identified three more market-related elements in addition to utility maximization, including budget constraints, competitive bidding, and endogenous relocation.

Budget constraints exist in the majority of the models reviewed. Some of them, however, implemented budget constraints indirectly by assuming, for example, that low-income households cannot afford housing in high-cost neighborhoods (Benenson 1998; Benenson and Torrens 2004). The less frequently implemented market element is competitive bidding (eight out of thirty-one models; Waddell 2002; Miller et al. 2004; Kii and Doi 2005; Fossett 2006; Caruso et al. 2007; Filatova, Parker, and van der Veen 2009; Liggmann-Zielinska 2009; Magliocca et al. 2011). Even those models that included budget constraints and competitive bidding often had no endogenous land price mechanism and thus misrepresented one of the most fundamental market functions. For example, some models derive land prices using a theoretical and linear distance-decay gradient or by calculating average prices across some administrative or planning zones (e.g., Miller et al. 2004; Liggmann-Zielinska 2009).

In addition to budget constraints and competitive bidding, relocation also drives the LM by shaping both the demand and supply sides. Relocation has received more attention than competitive bidding (seventeen vs. eight models), especially in models developed by geographers and demographers (Benenson 1998; Benenson and Torrens 2004; Fossett 2006; Diappi and Bolchi 2008). Most relocation models have rather simple market processes and few represent the interaction between households and the market. Some treat relocation as an exogenous factor controlled by population dynamics, mobility rates, or changes in the life courses of agents (Torrens 2006, 2007), whereas others take relocation as the result of the mismatch between actual and preferred ethnic composition in the local neighborhood (Fossett 2006). Although we acknowledge the importance of endogenous relocation, we see it as part of a dynamic market that evolves from a series of static, short-run markets. Our current modeling focuses on these short-run equilibriums. An extension, in which endogenous relocation and other population dynamics drive the long-term evolution of an LM, is under development.

Despite the relative abundance of market-related LUC models, they do not collectively provide
understanding of the effects that different implementations of LMs have on model outputs, begging the question of whether markets could significantly alter LUC model outputs and how differently each market element behaves in these models. To address this question, we designed LUXE, which incrementally incorporates utility maximization, budget constraints (BC), and competitive bidding (CB) to determine whether representation of different elements of LMs matter and how they might influence model outputs. Varying the presence of BC and CB generated four levels of market representation (Table 2): L0 (including none of BC and CB), L0.5 (including only CB), L1 (including only BC), and L2 (including both). As we regarded utility maximization as the fundamental, defining element for a “market” model, it was in all four market levels. By analyzing outputs from each of the four levels, we directly compared the effects of LM representation as well as the individual effects of CB and BC (more details are given later).

### Methods

LUXE combines features of two existing models. The first, ALMA, focuses on LM interactions and the microeconomic determinants of willingness to pay (WTP) and willingness to accept (WTA; Filatova, van der Veen, and Parker 2008; Parker and Filatova 2008).
Table 2. Market-level definition

<table>
<thead>
<tr>
<th>Market level</th>
<th>Without competitive bidding</th>
<th>Competitive bidding</th>
</tr>
</thead>
<tbody>
<tr>
<td>Without budget constraints</td>
<td>L0</td>
<td>L0.5</td>
</tr>
<tr>
<td>Budget constraints</td>
<td>L1</td>
<td>L2</td>
</tr>
</tbody>
</table>

Note: Adapted from Parker, Brown, et al. (2012).

The second, SOME, uses survey and spatial data to develop empirically based utility and suitability measures for land buyers, then uses these measures to sequentially allocate LUC events (Brown and Robinson 2006; Brown et al. 2008; Filatova, van der Veen, and Parker 2009; Robinson and Brown 2009). LUXE expands on both and implements utility maximization, budget constraints, and competitive bidding. LUXE is written in Java and can be integrated with Repast Simphony. Although LUXE serves as a supporting module in larger systems, it also operates as an independent ABM of LUC, featuring a relatively complex land market mechanism and auxiliary geographic information system (GIS) and landscape components.

Land Markets and Agents

LUXE is a monocentric city model that contains a landscape, agents, and institutions. The choice of a monocentric model was driven by two factors. First, we wanted to keep the simulation model as simple as possible, while still being able to answer the main research questions. We do not expect that extending LUXE to a polycentric model would qualitatively change our main findings, although this question could be investigated in future work. Second, the monocentric model allows us to compare simulation results to a benchmark analytical model, a strategy recommended in agent-based computational economic analysis literature (Axtell 2005; Tesfatsion 2006; Parker forthcoming).

The LUXE landscape is a rectangular space divided into regular grid cells. Each cell is either rural/agricultural or urban/residential and represents a parcel of land. Accordingly, there are two types of agents, rural landowners (RLOs) and residential household agents (RHAs). Each rural land parcel is claimed by an RLO, each urban parcel is occupied by an RHA, and only one agent is allowed for each parcel.

In North America, the process of land development involves land developers and home builders not represented in the specific version of the model discussed in this article (Henderson and Thisse 1999; Weiss 2002; Brown et al. 2008; Parker, Sun, et al. 2012). To focus on comparing the theoretical effects of different residential market representations, we simplify the process by assuming that developers and homebuilders are homogenous, rational, and function perfectly in terms of bridging supply of RLOs and demand from RHAs. This assumption underlies mainstream analytical and econometric models in land economics. With the same assumption, experiments presented in this article can provide insights into the role of LM while allowing comparison with equilibrium-based LUC models.

LUXE explicitly implements a listing service institution, which coordinates and records all of the listing, searching, bidding, and transaction tasks (Figure 1). When RLOs want to sell their land, they form listing prices and put their properties on the market. RHAs then search the market listing and bid on the property within their budget that gives them the highest utility (explained later). RLOs accept the bid from the highest bidder, if that bid exceeds their reservation price. Once the transaction is completed, the RHA transfers the appropriate resources to the seller, land use on the transacted property changes from rural to urban, and land ownership is updated. When no more land exchanges are possible, the market reaches a short-run equilibrium state and the model stops running (Parker and Filatova 2008; Robinson et al. 2013).

The key behavioral aspects of the model are how RHAs evaluate land parcels to determine their utility and how they determine bidding prices (based on their WTP). Among numerous real-world socioeconomic and environmental factors, we focus only on two, open-space amenities (OSA) in the local neighborhood and proximity to the urban center (PUC), which have been empirically demonstrated to significantly affect land utilities and prices (Capozza and Helsley 1989; Cheshire and Sheppard 1995; Geoghegan 2002; Anderson and West 2006). OSA ($A_i$) are calculated as the density of undeveloped land ($L^u_i$) in a circular neighborhood with radius $r$ and PUC ($P_i$) as one minus the standardized Euclidean distance to the urban center (Equations 1 and 2, respectively). Both are scaled to $[0, 1]$ by definition.

\[
A_i = \frac{\sum_{T_i < T_N} L^u_T}{\sum_{T_i < T_N} L_T} \quad (1)
\]

\[
P_i = 1 - \frac{\text{dist}(i)}{\max(\text{dist})} \quad (2)
\]
The utility for RHAs from acquiring a particular parcel is determined by a Cobb–Douglas (CD) function (Equation 3), where \( \alpha_k, \beta_k \) are the agent’s preferences for OSA and PUC, with \( 0 < \alpha_k, \beta_k < 1 \), and \( \alpha_k + \beta_k = 1 \). For agent \( k \), the utility for parcel \( i \) is as follows.

\[
U_i^k = A_i^{\alpha_k} \cdot P_i^{\beta_k} \tag{3}
\]

Among the numerous forms of utility functions, the variants of CD and linear utility functions (similar to...
multicriteria evaluation in nonmarket LUC models) are popular in ABM of LUC (Carver 1991; Store and Kangas 2001; Veldkamp and Lambin 2001; Brown and Robinson 2006; Filatova, van der Veen, and Parker 2009). One drawback of linear functions, however, is that they assume complete, linear substitutability. Even if the suitability of one factor drops to zero, the whole utility could still be well above zero (Brown and Robinson 2006). By contrast, the CD functional form has no such limitation and is also standard in economics (Fujita and Thisse 2002; Wu and Plantinga 2003). Its use here allows for comparison to other work while varying LM levels. The limits of CD are acknowledged, however, as the preference coefficients symbolize not only the strength of attractiveness of a certain locational attribute but also a share of budget an agent is willing to pay for it.

In our experiment, we assumed a homogeneous reservation price or WTA for acquisition of a rural land parcel (Filatova, Parker, and van der Veen 2009; Magliocca et al. 2011). The buyer’s WTP is then represented by:

$$p_k^i = (Y_k - d \cdot c_{ud}) \cdot \frac{U_k^{i2}}{U_k^{i2} + b_k}$$

(4)

where $p_k^i$ is the WTP of agent $k$ for land parcel $i$, $Y_k$ is the agent’s budget, $d$ is distance from parcel $i$ to the urban center, $c_{ud}$ is the unit-distance transport cost, and $U_k^{i2}$ is the utility (Equation 3). The share of a household’s budget expended on the house versus all other goods is controlled by a constant budget splitting factor $b_k$ that determines the convexity of the WTP for housing. This function is qualitatively similar to a traditional demand function derived from budget-constrained utility maximization (Parker and Filatova 2008; Filatova, Parker, and van der Veen 2009; Parker, Brown, et al. 2012).

Parameterization and Experimental Design

The experiments presented in this article are primarily theoretical. In contrast to empirical ABMs, which are calibrated and validated using real-world data, processes, and patterns, theoretical ABMs are usually verified using standard software testing routines and well-understood theoretical cases (Manson 2003; Manson, Sun, and Bonsal 2012). We also followed such methods. In particular, we calibrated model parameters with a combination of mathematical reasoning and parameter sweeping and verified every unit or module with testing, including ensuring that a version of the model could replicate results from ALMA, written in Netlogo (Filatova, Parker, and van der Veen 2009). Finally, we structurally validated LUXE as it produced the exact same land change patterns as the analytical von Thünen model in the case of homogenous buyers without spatial externalities.

Three categories of parameters were used to initialize LUXE: a set that is constant for all model runs (Group I in Table 3); a set that controls variation in the agents’ characteristics, the economic environment, and the spatial environment (Group II.a); and a set that varies in ways that define the four levels of market representation (Group II.b). Although the constant parameters can significantly alter the outcomes of LUXE, their impacts can be shown either theoretically or analytically to be largely predictable. By contrast, the other two groups of parameters are tightly linked to market behaviors and interact with each other, exhibiting typical characteristics of nonlinear complex systems. We therefore conducted multiple model runs that incrementally varied the values of the nonconstant parameter groups to examine their influence on the model outcomes. Chosen parameter values were selected to balance the breadth and the representativeness of all experimental cases, with the goal of drawing concrete and robust conclusions (see the Appendix for Group I and Group II.a parameter values).

The parameters that were used to represent the four market levels included (1) the number of land parcels that a buyer chooses to evaluate—to allow for utility maximization, (2) the seller’s WTA value—to represent absence or presence of the budget constraint (BC), and (3) the maximum number of bids allowed on a parcel—to operationalize competitive bidding (CB).

Market level 0 (L0) has no BC or CB. In L0, the number of parcels selected by a buyer for evaluation ($N_{ib}$) is set to all available parcels. The reservation price of agricultural land $P_{ag}$ is set much lower than buyers’ minimum budgets so that every buyer can afford any parcel in the landscape. L0 essentially implements sequential allocation of parcels according to buyers’ preference ranking.

Market level 0.5 (L0.5) adds CB, but without imposing BC. The maximum number of bids allowed on a parcel (max $N_{bd}$) controls whether CB takes place. In L0.5, max $N_{bd}$ is higher than one, meaning that a seller will receive multiple offers. The highest bid (i.e., WTP) wins the parcel, if it is above the seller’s reservation WTA.

Market level 1 (L1) imposes BC on buyers but with no CB, leading to budget-constrained first-come,
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Table 3. Key input parameters for LUXE model

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Meaning</th>
<th>Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>I. Constant parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$S_L$</td>
<td>Size of the simulated landscape</td>
<td>49</td>
</tr>
<tr>
<td>$N_R$</td>
<td>Number of residential households (buyers)</td>
<td>400</td>
</tr>
<tr>
<td>$N_s$</td>
<td>Number of rural land owners (sellers)</td>
<td>2,401 ($49 \times 49$)</td>
</tr>
<tr>
<td>$\delta \beta$</td>
<td>The range of preference for proximity $\beta_u$, bounded by $[\beta_u - \frac{\delta \beta}{2}, \beta_u + \frac{\delta \beta}{2}]$</td>
<td>0.20</td>
</tr>
<tr>
<td>$b_u$</td>
<td>Budget splitting factor for nonhousing consumption</td>
<td>0.6</td>
</tr>
<tr>
<td>$C_t$</td>
<td>Transport cost per unit-distance</td>
<td>1.00</td>
</tr>
<tr>
<td>II. Varied parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>II.a Household-level parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\overline{B}$</td>
<td>Mean budget for buyers</td>
<td>120, 140, 160, 180, 200</td>
</tr>
<tr>
<td>$\sigma_B$</td>
<td>Standard deviation of budget $B$</td>
<td>50</td>
</tr>
<tr>
<td>$\overline{\beta}_u$</td>
<td>Mean value of preference for proximity in utility calculation</td>
<td>0.2, 0.5, 0.8</td>
</tr>
<tr>
<td>$\sigma_{\beta_u}$</td>
<td>Standard deviation of $\overline{\beta}_u$</td>
<td>0.1</td>
</tr>
<tr>
<td>$r_N$</td>
<td>The radius of the circular neighborhood in the calculation of open-space amenity</td>
<td>1, 2, 3</td>
</tr>
<tr>
<td>II.b Market-level parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$N_{sp}$</td>
<td>The maximum number of parcels that a buyer evaluates for bidding</td>
<td>2,401, 2,401, 2,401, 2,401</td>
</tr>
<tr>
<td>$P_{ag}$</td>
<td>Agricultural reservation price, WTA</td>
<td>0, 0, 100, 100</td>
</tr>
<tr>
<td>$N_{bd}^{\text{max}}$</td>
<td>Number of bids allowed for one parcel</td>
<td>1, 400, 1, 400</td>
</tr>
</tbody>
</table>

Note: WTA = willingness to accept.

first-served preference-based land allocation. The RLO’s WTA ($P_{ag}$) is set at a level that poses a limitation on some low-budget buyers’ choices. Only one bid is allowed for each land parcel and the first bidder will succeed in purchasing the parcel if her bid price is higher than the seller’s WTA.

Market level 2 (L2) combines BC and CB. Buyers each bid on the highest utility parcel that is affordable under BC, and sellers accept the highest bid, provided it exceeds their WTA.

Analysis of Output

With LUXE, we simulated LUC outcomes for the four market levels (Tables 2 and 3). We then analyzed differences in outcome metrics across these levels by applying statistics, regression, and visualization. Model experiments were replicated fifty times with different random seeds to capture the variability in outcomes associated with heterogeneity in agents’ budgets and preferences.

To compare model outputs under different market representation levels, we calculated a series of nonspatial and spatial measures to describe the quantity of LUC ($Q$) and its spatial patterns. $Q$ can be either exogenous or endogenous in LUXE, depending on the market level and model parameters. In some market scenarios, where every buyer acquires a parcel, $Q$ is essentially exogenous and fully determined by the number of buyers. Whenever budget constraints are imposed, a certain proportion of buyers (depending on market conditions) do not participate in the LM, and $Q$ becomes endogenous.

We chose standard fragmentation measures to depict and compare the spatial patterns of projected LUC. Although the definition and measurement of real-world patterns of fragmentation and sprawl are fiercely contested issues across disciplines (e.g., Galster et al. 2001; Ewing, Pendall, and Chen 2003; Parker and Meretsky 2004; Torrens 2008), we argue that several commonly used metrics effectively depict relevant dimensions of the spatial patterns of our simulated landscapes (Table 4). They are transport cost, landscape shape index, fractal dimension, edge density, and the adjacency, contiguity, and centrality indexes (see Appendix for definitions and Table 5 and Figure 2 for representative cases). To address the issue of comparing landscapes of different sizes across experimental settings (Saura and Martinez-Millan 2001), we also construct and report quantity-controlled version of several of these metrics.

We used a top-down, general-to-specific, and descriptive-to-analytical strategy to address the high
Table 4. Key model output metrics

<table>
<thead>
<tr>
<th>Name</th>
<th>Explanation</th>
<th>Correlation with fragmentation or sprawl</th>
<th>Impacts of landscape size</th>
<th>Value range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantity of converted land (Q)</td>
<td>Number of land-use change</td>
<td>N/A</td>
<td>N/A</td>
<td>[0, ∞)</td>
</tr>
<tr>
<td>Transport cost (C_{tran})</td>
<td>Transportation cost to the urban center</td>
<td>Positive</td>
<td>Very high</td>
<td>[0, ∞)</td>
</tr>
<tr>
<td>Landscape Shape Index (LSI, LSI_p)</td>
<td>The ratio of the total edge length to the possibly minimum edge length</td>
<td>Positive</td>
<td>High</td>
<td>[0, 1)</td>
</tr>
<tr>
<td>Fractal dimension (d_f)</td>
<td>The fractal dimension of developed land</td>
<td>Positive</td>
<td>Low</td>
<td>[1, 2]</td>
</tr>
<tr>
<td>Edge density (ρ_e)</td>
<td>The average linear distance of edges for all cells</td>
<td>Positive</td>
<td>Low</td>
<td>(0, 4)</td>
</tr>
<tr>
<td>Aggregation index (AI, AI_p)</td>
<td>Ratio of the total cell adjacencies to the possibly maximum adjacencies</td>
<td>Negative</td>
<td>High</td>
<td>(0, 1)</td>
</tr>
<tr>
<td>Contiguity index (CI, CP)</td>
<td>Average cell connectedness within a three by three moving window</td>
<td>Negative</td>
<td>Low</td>
<td>[0, 1]</td>
</tr>
<tr>
<td>Centrality (CTI)</td>
<td>The ratio of the radius of the possibly minimum circle to the actual radius</td>
<td>Negative</td>
<td>High</td>
<td>(0, 1)</td>
</tr>
<tr>
<td>Quantity-controlled and distance-weighted edge density (ρ_{e,q})</td>
<td>Average linear distance of edges for each of the first q land-use changes weighted by distance to the urban center</td>
<td>Positive</td>
<td>Low</td>
<td>[0, ∞)</td>
</tr>
</tbody>
</table>

Table 5. Measures from six representative landscapes

<table>
<thead>
<tr>
<th>Case</th>
<th>Q</th>
<th>C_{tran}</th>
<th>C_{max}</th>
<th>LSI</th>
<th>ρ_e</th>
<th>d_f</th>
<th>1 – AI</th>
<th>1 – CI</th>
<th>1 – CTI</th>
<th>ρ_{e,q}</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>161</td>
<td>6.653</td>
<td>11.402</td>
<td>11.769</td>
<td>3.801</td>
<td>1.980</td>
<td>0.946</td>
<td>0.669</td>
<td>0.380</td>
<td>2.071</td>
</tr>
<tr>
<td>B</td>
<td>173</td>
<td>7.165</td>
<td>13.454</td>
<td>8.630</td>
<td>2.694</td>
<td>1.847</td>
<td>0.646</td>
<td>0.667</td>
<td>0.459</td>
<td>1.630</td>
</tr>
<tr>
<td>C</td>
<td>194</td>
<td>5.423</td>
<td>9.487</td>
<td>1.607</td>
<td>0.464</td>
<td>1.182</td>
<td>0.047</td>
<td>0.129</td>
<td>0.177</td>
<td>0.256</td>
</tr>
<tr>
<td>D</td>
<td>200</td>
<td>5.802</td>
<td>10.817</td>
<td>3.966</td>
<td>1.150</td>
<td>1.529</td>
<td>0.232</td>
<td>0.283</td>
<td>0.255</td>
<td>0.643</td>
</tr>
<tr>
<td>E</td>
<td>215</td>
<td>8.103</td>
<td>15.620</td>
<td>7.267</td>
<td>2.028</td>
<td>1.747</td>
<td>0.470</td>
<td>0.547</td>
<td>0.472</td>
<td>1.256</td>
</tr>
<tr>
<td>F</td>
<td>226</td>
<td>9.789</td>
<td>17.493</td>
<td>12.677</td>
<td>3.478</td>
<td>1.948</td>
<td>0.860</td>
<td>0.869</td>
<td>0.515</td>
<td>2.418</td>
</tr>
</tbody>
</table>

Note: AI, CI, and CTI are presented as 1 – AI, 1 – CI, and 1 – CTI to make values in the table positively correlated to sprawl or fragmentation. AI = aggregation index; CI = contiguity index; CTI = centrality index.

dimensionality of the modeled data (i.e., space, time, input parameters, and output metrics). We first used descriptive statistics and linear regression to illustrate the overall impacts of markets on LUC outcomes. Descriptive statistics gave a relatively clear picture of the effects of market representation; however, they were limited to an aggregate picture of the outcome space. As the effects of market representation might vary across model parameters, we applied regression that is normally applied to empirical observations to inductively estimate relationships between model parameters and model outputs (Axelrod 1997; Parker forthcoming). To examine and compare outputs from individual runs with different parameter settings, we also applied a visualization technique we termed comprehensive plotting to assemble results from multiple sets of parameters into a single plot to illustrate the impacts of four market levels on a single output metric, averaged across fifty runs per each set of parameters. Comprehensive plotting not only verified conclusions drawn from statistics and regression but visualized model sensitivity and helped identify conditions that produced anomalies.

**Results**

The presentation of our results focuses on how LUC quantity and spatial patterns vary across the four levels of market representation. Our chosen spatial metrics were organized into three groups—overall spread, local fragmentation, and quantity-controlled metrics—that depict different aspects of the simulated LUC patterns. The effects of market representation levels, through the presence of budget constraints (BC) and competitive bidding (CB), were examined separately for each of these grouped spatial metrics.

**Descriptive Statistics**

We grouped output pattern measures by land market representation levels and calculated their mean values.
and standard deviations, as well as levels of statistically significant difference among market levels under the same combinations of model parameters (Table 6).

**Quantity of Change.** The addition of market elements (from L0 to L2) decreased the mean quantity of converted land (Q) by 47 percent (from 400 to 211 parcels).

- CB alone (moving from L0 to L0.5) did not affect Q, as without BC, each RHA could acquire an acceptable parcel (although perhaps not in their most preferred location).
- The introduction of BC (L0 to L1) reduced Q by about 44 percent relative to L0 and L0.5 because many parcels were not affordable for RHAs. BC essentially prevented conversion of a ring of parcels at the urban–rural fringe, whose opportunity cost of conversion (agricultural value) exceeded the real buying power of RHAs (compare Figure 3A to Figure 3C).
- CB, in addition to BC (L1 to L2), further reduced Q by another 3 percent. In this case the RHAs with the strongest preferences for PUA over OSA, and with relatively high budget offered the highest bid on the converted parcels. As in L0, other agents, having been outbid for these parcels, were left to consider parcels that were not their first choice. Now also facing BC, however, some RHAs found that their valuation for their highest utility parcel (dependent on their budget) fell below the seller’s WTA. In this “open city” model, those RHAs then decided not to purchase properties and could not locate anywhere on the landscape.

Although CB alone had no impact on Q, it helped reveal the gradient of land prices through market sorting. BC, by contrast, prevented all economically implausible transactions and therefore reduced Q, yet
could not change the shape of the price gradient (Figure 3).

**Spatial Patterns of Change.** Compared with Q, spatial outcome measures produced less consistent results and revealed the multidimensional spatial complexity widely understood to characterize sprawl (Table 6). Based on consistencies in the same qualitative changes in metric values (i.e., increase or decrease) across market levels, we identified three groups of metric values that represent three dimensions of the simulated landscape patterns (Figure 4).

The first dimension (T1) includes the metrics of average and maximum transport costs (C_{tran} and C_{tran}^\text{max}), as well as landscape shape index (LSI). We interpret this dimension as the overall spread of the simulated landscapes, which is generally related to the development density and the overall spatial coverage of the LUC. The second dimension, which includes edge density (\rho\_e), fractal dimension (d\_f), aggregation index (AI), centrality index (CI), and contiguity index (CTI), describes the local pattern of fragmentation (T2 in Figure 4). The quantity-controlled metrics show yet a separate dimension (T3) from the noncontrolled metrics. We separately examine how market levels and their defining elements generate these dynamics.

**Overall Spread.** The L2 LM, with both BC and CB, led to a statistically significant decrease (compared to L0) in the overall spread as measured by C_{tran} and C_{tran}^\text{max}, and LSI (Table 6) and visualized by T1 (Figure 4).

- CB drove more spread in the absence of BC (L0.5 > L0 in T1, Figure 4). Compared to L0, L0.5 showed a 2.7 percent increase in C_{tran}, 1.2 percent increase in C_{tran}^\text{max}, and more than 4 percent increase in LSI. Intuitively, buyers who were not able to obtain their first choice parcel, but were not budget-constrained, located farther away from the urban center, trading off the value of proximity for increased OSAs.
- Imposing BC (compare L0 to L1 and L0.5 to L2 in T1 in Figure 4) reduced spread. BC consistently reduced C_{tran} and C_{tran}^\text{max} (for about 20 percent on average), as well as LSI (17 percent from L0 to L1, or 21 percent from L0.5 to L2).
- Adding CB to BC (L1 to L2) fostered a decrease in spread (L2 < L1 in T1). The magnitude of change is lower than that induced by BC alone, however, as indicated by a 0.6 percent decrease in C_{tran}, a 2.2 percent decrease in C_{tran}^\text{max}, and a 0.7

### Table 6. Comparison of measures from market levels, mean value and standard deviation

<table>
<thead>
<tr>
<th>Market levels</th>
<th>L0</th>
<th>L0.5</th>
<th>L1</th>
<th>L2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantity Q</td>
<td>400 (0)</td>
<td>400 (0)</td>
<td>223 (44)</td>
<td>211 (46)</td>
</tr>
<tr>
<td>T1: Overall spread</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C_{\text{tran}} &amp; 9.84 (1.94)</td>
<td>10.11 (2.22) &amp; 7.80 (1.90) &amp; 7.75 (2.14)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C_{\text{tran}}^\text{max} &amp; 17.92 (3.77)</td>
<td>18.13 (4.19) &amp; 14.39 (3.54) &amp; 14.08 (3.85)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LSI &amp; 10.86 (6.17)</td>
<td>11.31 (6.05) &amp; 9.03 (5.53) &amp; 8.97 (4.31)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T2: Local fragmentation</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>d_f &amp; 1.724 (0.25)</td>
<td>1.740 (0.23) &amp; 1.763 (0.25) &amp; 1.771 (0.22)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>\rho_e &amp; 2.17 (1.23)</td>
<td>2.26 (1.21) &amp; 2.46 (1.18) &amp; 2.51 (1.14)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AI &amp; 0.481 (0.33)</td>
<td>0.457 (0.32) &amp; 0.414 (0.32) &amp; 0.402 (0.31)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CI &amp; 0.523 (0.25)</td>
<td>0.504 (0.25) &amp; 0.455 (0.24) &amp; 0.445 (0.23)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CTI &amp; 0.648 (0.12)</td>
<td>0.645 (0.13) &amp; 0.605 (0.12) &amp; 0.606 (0.12)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>T3: Quantity-controlled sprawl</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LSI &amp; 8.846 (6.77)</td>
<td>6.450 (2.88) &amp; 8.221 (1.48) &amp; 6.550 (2.81)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>\rho_e &amp; 3.56 (0.89)</td>
<td>1.69 (0.81) &amp; 2.78 (0.97) &amp; 1.70 (0.79)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AI &amp; 0.128 (0.09)</td>
<td>0.389 (0.32) &amp; 0.198 (0.16) &amp; 0.383 (0.31)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CI &amp; 0.130 (0.06)</td>
<td>0.415 (0.23) &amp; 0.210 (0.12) &amp; 0.412 (0.22)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: These metrics are grouped according to their relative values among market levels and their indicative properties to various dimensions of sprawl. + means the metric is positively correlated to sprawl/spread/fragmentation. – means negatively. LSI = landscape shape index; AI = aggregation index; CI = contiguity index; CTI = centrality index.

*Significant at 0.1.
**Significant at 0.01.
***Significant at 0.001 with Wilcoxon Signed-Rank Test and a null hypothesis that measures from L0.5, L1, and L2 have the same distribution as L0.
†, ‡, and †† are L1 and L2 against L0.5.
††, ‡‡, and ††† are L2 against L1.
percent decrease in LSI. In parallel with the intuition about the reduction in urban conversion in an L2 market representation, spread is reduced because less competitive RHAs find their relatively distant second-best parcels unaffordable (high transport cost) given their budget constraints or unfavorable (low utility) because of low proximity.

Overall, the effects of additional market elements on spread are nonmonotonic and depend on the in-
Figure 4. Three dimensions of landscape pattern measures: Overall spread (average and maximum transport cost, landscape shape index), fragmentation (fractal dimension, edge density, aggregation index, contiguity index, centrality index), and quantity-controlled metrics. Note: We standardized each metric between zero and one, calculated their means across all metrics in the category, and plotted these averages for each metric group across each market level. These mean values are indicative of three dimensions of the spatial patterns and are only valid for comparison purposes, as they are essentially the average of related but different spatial measures by definition.

Interplay between budget constraints and competitive bidding.

**Fragmentation.** The five fragmentation metrics—\( \rho_e, d_f, AI, CI, \) and CTI—show a distinct pattern from that for spread. The introduction of the L2 LM increased fragmentation compared to L0, with \( d_f \) and \( \rho_e \) increasing 2.7 percent and 15.7 percent, respectively, and AI, CI, and CTI decreasing 16.4 percent, 14.9 percent, and 6.5 percent, respectively. All measures changed monotonically with the degree of market representation, consistently demonstrating an increase in fragmentation (T2 in Figure 4).

- CB without BC (L0 to L0.5) led to a 0.93 percent and 4.2 percent increase in \( d_f \) and \( \rho_e \), respectively, and a 5 percent and 3.4 percent decrease in AI and CI, respectively. Intuitively, the sorting mechanism provided by competitive bidding might better allocate buyers across the landscape in a way that accounts for their preference for being surrounded by OSAs (a more fragmented landscape).
- BC without CB (L0 to L1) increased fragmentation, with a respective 2.3 percent and 13.4 percent increase in \( d_f \) and \( \rho_e \) and a respective 13.9 percent, 13 percent, and 6.7 percent decrease in AI, CI, and CTI. The increased fragmentation is primarily explained by the fact that BC resulted in a smaller urban footprint (i.e., smaller \( Q \)) that also reduced fill-in development. As seen in Figure 3A (L0) and Figure 3C (L1), BC not only produced a smaller urban extent, but also prevented some LUCs around urban land parcels (the blur bars in Figure 3A). As discussed later, when \( Q \) was controlled, BC reduced fragmentation.
- Adding CB to BC (L1 to L2) increased fragmentation above the level measured with only BC. This additional increase in fragmentation is relatively small compared to the levels measured when only BC were included (L1). Whereas CTI had no statistically significant change, \( d_f \) and \( \rho_e \) increased by 0.7 percent and 3.1 percent, respectively, and AI and CI decreased by 3.9 percent and 2.3 percent, respectively. This effect likely represented the combined influences of the two effects discussed earlier.

It must be noted that these standardized local measures are more related to complexity and fragmentation of the landscape rather than to its overall spread discussed earlier. A landscape pattern could be more spreading but less fragmented (e.g., Figure 2A and 2B).

**Quantity-Controlled Spatial Metrics.** The quantity-controlled metrics include one metric from T1 measuring spread (LSIq) and three metrics from T2 measuring fragmentation (\( \rho_{eq}, AIq, \) and \( CIq \)). Yet, all four measures demonstrated the same trends. No monotonic relationships between market level and fragmentation were seen. Both CB and BC independently decreased sprawl, and the net effects of an introduction of both market elements (L0 to L2) was a decrease in fragmentation: a 26 percent and 52 percent decrease in LSIq and \( \rho_{eq} \), and a 199 percent and 217 percent increase in the AIq and CIq, respectively.

- The introduction of CB without BC (L0 to L0.5) accounted for the majority of decrease observed in the quantity-controlled sprawl metrics. LSIq and \( \rho_{eq} \) decreased by 27 percent and 53 percent, respectively. AIq and CIq increased by 204 percent and 219 percent, respectively. These results indicate that the sorting mechanism provided by CB substantially reduced the degree of urban sprawl projected by LUC models.
• BC in the absence of CB (L0 to L1) reduced sprawl, but by a small magnitude. \( LSI^p \) and \( \beta_3^p \), respectively, by 7 percent and 21 percent. \( AI^p \) and \( CI^p \), respectively, by 55 percent and 62 percent.

• Although adding CB to BC (L1 to L2) reduced sprawl with quantity control, it did not lead to a statistically significant decrease in sprawl relative to L0.5. This might imply that there are no significant interaction effects between BC and CB in terms of their effects on projected sprawl. This conclusion, however, only applies to the early stage of urban land development, as we intentionally froze land development at the minimum quantity across four market levels. Without quantity controls, more land will be developed and there will be occasions of fill-in development. In that case, as discussed earlier, CB might reduce LUC and induce more fragmented spatial patterns.

### Linear Regression Analysis

We ran four ordinary least square (OLS) regressions of main input parameters on \( Q \), \( \bar{C}_{trans} \), \( \rho_e \), and \( \rho_e^q \) to examine how the influence of market levels varies with other factors. The dependent variables for the OLS were individual preferences for PUC (\( BC \)) and their mean preferences for PUC (\( CB \)). The four market elements, BC and CB, were added as two dummy variables \( BC_{dv} \) (1 for with budget constraints, 0 for without) and \( CB_{dv} \) (1 for with competitive bidding and 0 for without). Their interaction term (\( BCCB_{dv} \)) was also added as a dummy variable. The three dummy variables, therefore, can effectively differentiate the four market levels that the model implemented. The four OLS regressions are

\[
Q = \beta_1 + \beta_1^1 \cdot BC_{dv} + \beta_2^1 \cdot BC_{dv} + \beta_3^1 \cdot BCCB_{dv} + \beta_4^1 \cdot BC_{dv} \cdot B + \beta_5^1 \cdot \bar{B} + \beta_6^1 \cdot r_N + \varepsilon_Q (5)
\]

\[
\bar{C}_{trans} = \beta_3 + \beta_2^2 \cdot BC_{dv} + \beta_3^2 \cdot BC_{dv} + \beta_3^2 \cdot BCCB_{dv} + \beta_3^3 \cdot BCCB_{dv} + \beta_3^4 \cdot BC_{dv} \cdot B + \beta_3^5 \cdot \bar{B} + \beta_3^6 \cdot \bar{B} + \beta_3^7 \cdot r_N + \varepsilon_C (6)
\]

\[
\rho_e = \beta_3 + \beta_3^1 \cdot BC_{dv} + \beta_3^2 \cdot BC_{dv} + \beta_3^3 \cdot BCCB_{dv} + \beta_3^4 \cdot BC_{dv} \cdot B + \beta_3^5 \cdot \bar{B} + \beta_3^6 \cdot \bar{B} + \beta_3^7 \cdot r_N + \varepsilon_\rho (7)
\]

\[
\rho_e^q = \beta_3 + \beta_3^1 \cdot BC_{dv} + \beta_3^2 \cdot BC_{dv} + \beta_3^3 \cdot BCCB_{dv} + \beta_3^4 \cdot BC_{dv} \cdot B + \beta_3^5 \cdot \bar{B} + \beta_3^6 \cdot \bar{B} + \beta_3^7 \cdot r_N + \varepsilon_\rho^q (8)
\]

All four had good fit, indicated by adjusted \( R^2 \) values of 0.99, 0.91, 0.95, and 0.95, respectively (Table 7).

### Quantity of Change

Consistent with descriptive statistics, market elements reduced the projected \( Q \), with BC playing the dominant role.

• CB alone (L0 to L0.5) had no statistically significant impacts on \( Q \) (\( \beta_3^1 = 0 \)).

• The imposition of BC (L0 to L1) significantly reduced \( Q \), with a negative coefficient of \( \beta_3^1 = -592.4 \). Omitting BC, therefore, is likely to overproject the magnitude of LUC. When there are BC, higher budget levels allow more land to be developed (\( \beta_3^1 = 2.59 \)).

• When combined with BC, CB (L0 to L2) further reduced \( Q \) (\( \beta_3^1 = -11.38 \)).

Besides the level of market representation, agents’ preference for PUC had a statistically significantly negative impact on \( Q \). When buyers like living closer to the urban center, there will be less land developed. By contrast, the coefficient of the neighborhood size used to evaluate OSA was not significant, implying this parameter had little effect on \( Q \).

### Average Transport Cost (Overall Spread)

The trends that emerged from this regression qualitatively mirror those found in the descriptive statistics. Specifically, market representations reduced \( \bar{C}_{trans} \), but effects were nonmonotonic, and not all explanatory variables were significant.

• The impact of CB alone (L0 to L0.5) on \( \bar{C}_{trans} \) was not statistically significant. Yet, it had positive impacts (\( \beta_3^1 > 0 \)) as was also revealed by the statistics.

• BC generally reduced spread by decreasing \( \bar{C}_{trans} \) (\( \beta_3^5 = -8.009 \)). As expected, a higher mean budget level in RHAs led to higher \( \bar{C}_{trans} \) (\( \beta_3^5 = 0.037 \)).

• When combined with BC, the effect of CB on reducing \( \bar{C}_{trans} \) became statistically insignificant. This result highlights the importance of the regression approach in controlling for the independent variation in the data.

Beyond market elements, both neighborhood size and mean preference for PUC significantly reduced \( \bar{C}_{trans} \). Individual preferences for PUC were the second most influential factor affecting \( \bar{C}_{trans} \) in addition to BC, with \( \beta_3^5 = -7.305 \). Neighborhood size also had a statistically significant effect, but with a smaller influence (\( \beta_3^5 = 0.519 \)). Intuitively, if households prefer PUC
Table 7. Ordinary least squares regression on output measures

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>1. Quantity of land-use change</th>
<th>2. Average transport cost</th>
<th>3. Edge density</th>
<th>4. Q-controlled edge density</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant ($\beta_6$)</td>
<td>411.4 (2.608)**</td>
<td>12.456 (0.264)**</td>
<td>5.499 (0.103)**</td>
<td>5.326 (0.102)**</td>
</tr>
<tr>
<td>DV of competitive bidding ($\beta_1$)</td>
<td>0.000 (1.960)</td>
<td>0.274 (0.198)</td>
<td>0.089 (0.078)</td>
<td>-1.874 (0.076)**</td>
</tr>
<tr>
<td>DV of budget constraints ($\beta_2$)</td>
<td>-592.4 (9.798)**</td>
<td>-8.099 (0.991)**</td>
<td>1.099 (0.389)**</td>
<td>-2.011 (0.382)**</td>
</tr>
<tr>
<td>DV of constraints and bidding ($\beta_1$)</td>
<td>-11.38 (2.771)**</td>
<td>-0.324 (0.280)</td>
<td>-0.043 (0.110)</td>
<td>0.788 (0.108)**</td>
</tr>
<tr>
<td>Mean budget ($\beta_4$)</td>
<td>2.593 (0.060)**</td>
<td>0.037 (0.006)**</td>
<td>-0.005 (0.002)**</td>
<td>0.008 (0.002)**</td>
</tr>
<tr>
<td>Mean proximity preference ($\beta_5$)</td>
<td>-22.59 (2.829)**</td>
<td>-7.305 (0.286)**</td>
<td>-4.129 (0.112)**</td>
<td>-3.268 (0.110)**</td>
</tr>
<tr>
<td>Neighborhood size ($\beta_6$)</td>
<td>-0.056 (0.849)</td>
<td>0.519 (0.086)**</td>
<td>-0.631 (0.034)**</td>
<td>-0.064 (0.033)**</td>
</tr>
<tr>
<td>$R^2$ (adjusted)</td>
<td>0.995 (0.994)</td>
<td>0.906 (0.901)</td>
<td>0.945 (0.942)</td>
<td>0.946 (0.942)</td>
</tr>
</tbody>
</table>

Note: $N = 108$. DV = dummy variable.
*Significant at 0.1.
**Significant at 0.05.
***Significant at 0.01.
****Significant at 0.001.

---

over OSA, or they use a smaller neighborhood radius to assess land quality, the spatial pattern will be more compact than using a higher preference for OSA or a larger neighborhood. The larger the radius of the neighborhood an RHA considers, the higher the chance that more distant open-space areas add to the utility of an agent.

**Edge Density (Fragmentation).** Regression showed that market elements decreased spread but increased fragmentation. BC, as in the regression results for spread, played a dominant role, with CB having insignificantly small effects.

- CB in isolation (L0 to L0.5) led to a positive but statistically insignificant increase in $\rho_e$, again highlighting the importance of controlling for explanatory regressors.
- BC (L0 to L1) increased $\rho_e$ ($\beta_2 = 1.099$). Increase in budget levels decreased $\rho_e$; however, the coefficient ($\beta_4 = -0.005$) was only weakly significant.
- The activation of CB in addition to BC (L0 to L2) decreased $\rho_e$, but not to a statistically significant degree.

Buyers’ preference for proximity was a strong explanatory variable for $\rho_e$ variation ($\beta_5 = -4.129$). When buyers favor proximity, the landscape will be less fragmented. The coefficient of neighborhood size on $\rho_e$ was also statistically significant. Using larger neighborhood to assess OSA led to less fragmented land use patterns ($\beta_6 = -0.631$).

**Quantity-Controlled and Distance-Weighted Edge Density.** The results for our chosen quantity-controlled metric show somewhat similar patterns to the descriptive statistics, with one important exception.

- CB in isolation (L0 to L0.5) reduced $\rho_e^q$ ($\beta_4^q = -1.874$).
- The addition of BC independently also reduced $\rho_e^q$ by a comparable magnitude ($\beta_5^q = -2.011$). A one-unit increase in average budget led to a small but statistically significant increase of $\rho_e^q$ of 0.008 units, reflecting a higher willingness to pay for parcels surrounded by open space.
- In contrast to descriptive statistical results, the combination of BC and CB (L2) resulted in a smaller, but statistically significant increase in $\rho_e^q$. This implies that the net effect of the combination of BC and CB, after controlling the separate effects of these two market elements, was actually positive on fragmentation measure.

**Comprehensive Plotting**

In comprehensive plotting, the vertical axis shows the average value of the metric for each parameters’ set denoted in the horizontal table at the top of the plot. The gray vertical lines connect average values of the output metric to the parameter set that was used to generate them. The four curves denote the change of the output metric across the four market levels.
Quantity of Change. As noted before, CB alone (L0 to L0.5) did not reduce Q. Again, the comprehensive plot illustrated that BC (L1) reduced Q, and the addition of CB (L2) generally led to further, but smaller, reductions (Figure 5). The latter result did not always hold, however, and the anomalous outcomes represent a variety of specific situations (Figure 5). When buyers prefer OSA much more than PUC ($\bar{\beta}_u = 0.2$) and they use a relatively large neighborhood ($r_N = 3$), which incorporates the open-space value of more remote parcels, the addition of competition increased the amount of land conversion. One can observe this on three occasions, which are highlighted in green circles in Figure 5, where the line of market level L2 is above line L1.

At the same time, it is clear that neighborhood size had an interesting interaction with buyers’ preference for proximity. In the L2 market, if average agent preference for OSA was high (i.e., low preference for PUC $\bar{\beta}_u = 0.2$), an increase in the neighborhood size would increase Q (Figure 5, follow the green upward arrow where the L2 curve goes up as the neighborhood size increases from 1 to 3). When average agent preference for PUC was high ($\bar{\beta}_u = 0.8$), its impacts became negative (e.g., downward green arrow in Figure 5). In other words, when people prefer living close to the urban center and also consider open space over a broad radius to calculate utility, less land would be developed if they are financially constrained and compete with each other. This implies that fewer people buy—primarily because land that is both close to an urban center and has a high proportion of open space in the neighborhood will be relatively scarce. As a result, many buyer agents simply were not motivated to participate in the market. We characterize those with a strong preference for OSA over a larger neighborhood as “suburb lovers,” and those with a relatively high preference for PUA and close-in open space as “city lovers.” In general, a market representation with CB and BC is likely to increase projected sprawl for suburb lovers but decrease it for city lovers.

Average Transport Cost (Overall Spread). Consistent with descriptive statistics, comprehensive plots
Average Transportation Cost

<table>
<thead>
<tr>
<th>Var1</th>
<th>Var2</th>
<th>Mean Budget</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.2</td>
<td>0.5</td>
<td>140</td>
</tr>
<tr>
<td>0.5</td>
<td>0.8</td>
<td>160</td>
</tr>
<tr>
<td>0.8</td>
<td>0.2</td>
<td>180</td>
</tr>
<tr>
<td>0.2</td>
<td>0.5</td>
<td>140</td>
</tr>
<tr>
<td>0.5</td>
<td>0.8</td>
<td>160</td>
</tr>
<tr>
<td>0.8</td>
<td>0.2</td>
<td>180</td>
</tr>
<tr>
<td>0.2</td>
<td>0.5</td>
<td>140</td>
</tr>
<tr>
<td>0.5</td>
<td>0.8</td>
<td>160</td>
</tr>
<tr>
<td>0.8</td>
<td>0.2</td>
<td>180</td>
</tr>
</tbody>
</table>

Figure 6. Average transport cost under all market levels. (Color figure available online.)

illustrate that CB without BC (L0.5) increased $C_{\text{tran}}$ (Figure 6). These effects are most pronounced for the “suburb lovers.” To confirm descriptive statistics results: Imposing BC (L1) always reduced $C_{\text{tran}}$ (Figure 6). CB combined with BC (L2) reduced this measure in most situations. Again, competition only increased overall spread for those “suburb lovers.” When the neighborhood size was 3 and the preference for open space was 0.8 (preference for proximity is 0.2), $C_{\text{tran}}$ was significantly higher in L2 than in L1 (green oval in Figure 6).

**Edge Density (Fragmentation).** From the comprehensive plotting, it is clear that increasing market elements generally increased fragmentation (Figure 7), with some exceptions for those “suburb lovers” identified earlier. This is likely related to the fact that as open space was relatively scarce close to the urban center, the land further from the center delivered relatively low utility to RHAs, such that their WTP was below sellers’ WTA, and trade did not occur. BC (L1) consistently increased fragmentation above L0 and L0.5. The inclusion of both market elements (L2) had mixed effects compared to L1. Although it always showed a higher fragmentation level than L0.5, edge density was higher for L2 about half the time. These differences likely reflected quantity differences in the realized landscapes. Differences appear across sets of preferences for OSAs and proximity, however, consistent with the important role that these factors played in the regression results.

**Quantity-Controlled and Distance-Weighted Edge Density.** Consistent with descriptive statistics, the comprehensive plot for $\rho_q^e$ showed that BC reduced projected sprawl, as did CB, but their effects appear to be largely independent (Figure 8). Without competition, BC reduced fragmentation (i.e., L1 had a lower value than L0), in contrast to the slight increase seen in the non-quantity-controlled landscape (Figure 7). CB consistently produced more compact landscape patterns during the process of land development (Figure 8). Market levels L0.5 and L2, both of which implement competition, produced the lowest $\rho_q^e$, reinforcing the importance of representing this market element.
Discussion and Conclusion

LMs are made up of a number of mechanisms that give rise to complex interactions among buyers, sellers, and other actors involved in land exchanges. Researchers have attempted to represent markets to understand aspects of the complex land system. The most frequently implemented market elements in land-use models (as determined through literature review) include budget constraints and competitive bidding. We presented LUXE, a new, stylized ABM of LUC that was used to systematically alter the combination of these two market elements to evaluate their effects on the quantity and patterns of LUC in simulated landscapes. Our results revealed the significant yet complex effects of LMs on LUC patterns, illustrating the relationships between market representation and model outcomes under different assumptions of the agents’ heterogeneity in preferences and budgets, and the neighborhood size as well.

We used and compared three complementary methods—descriptive statistics, OLS regression, and comprehensive plotting—to analyze our data. These methods generally tell similar stories, but each provided a unique and useful view. Results from descriptive statistics and regressions were largely consistent, but some small differences emerged. The regression approach allowed us to not only control for but also formally examine the influence of other explanatory variables. For example, our estimated models showed that open-space preferences and neighborhood size remained important determinants of spatial outcomes, independent of the market representation. The use of comprehensive plots allowed us to examine the context-dependent cases, helped reveal how and under which conditions differences emerged, and provided an understanding of where exceptions to generalizations occurred, what role they played, and to what real-world circumstances they might be analogous.

Market elements in LUC models, particularly budget constraints and competitive bidding, can alter projected land-use patterns; their impacts on both quantity and spatial metrics were statistically significant under most conditions. Our results demonstrated that if
market elements were excluded from an LUC model, one might overproject the extent of LUC and the degree of sprawl in many circumstances. In general, we found that the endogenously generated quantity of LUC decreased with an increase in the level of market representation. Budget constraints played a dominant role in this process, and competitive bidding played a strong secondary role when budget constraints were present. Competitive bidding in the absence of budget constraints, however, might increase overall spread of simulated LUC. Thus, the direction of the impact of competitive bidding depended on whether buyer agents were financially constrained. Although the case of a completely budget-constraint-free for all is impossible in the real world, subprime mortgages through ill-regulated financial markets might be able to lift budget constraints for some in the short term.

The decreasing amount of land development resulting from increased representation of the market, however, did not guarantee a less fragmented landscape pattern. In contrast to what might be expected, increasing market representation, on average, actually produced more locally measured fragmentation. The introduction of budget constraints was responsible for 74 to 83 percent of change across four fragmentation metrics, with the activation of competitive bidding contributing the rest. When we controlled for the quantity of change, however, both budget constraints and competitive bidding reduced projected sprawl. Our experiments also showed that exceptions might occur when the neighborhood size is large and buyer agents have a high preference for open space, which is not uncommon in the cultural context of North America. In this case, the stronger market representation led to a higher degree of projected spread and fragmentation. In other words, market competition among buyers with a high preference for open space drove sprawl when they also used large neighborhoods to assess land quality. This is consistent with the expected interplay between high preferences for OSAs, the sorting that results from

Figure 8. Quantity-controlled and distance-weighted edge density under all market levels. (Color figure available online.)
competitive bidding, and the land scarcity that results from budget constraints.

The implications of our results for LUC research are twofold. First, the explicit representation of market elements in LUC models can alter our projection of LUC and characterization of the complexity inherent in coupled human–environment systems. Omitting LMs is likely to generate biased outputs in both the quantity of LUC and its spatial patterns. Second, the effects of LMs interact with many factors that are related to actors’ (and their virtual representation as agents) preferences and spatial configurations like neighborhood size. Researchers should be cautious to draw universal conclusions as they might overlook some critical dynamics and complex interactions in LMs and heterogeneous agents. Our experiments suggest that mechanisms at the core of a market institution and their pertinent market conditions should be examined individually and as a whole to understand the functioning of LMs and their impacts on LUC.

Although our developed model is deliberately abstract, we anticipate that these conclusions will also apply to empirically parameterized models used for planning and policy analysis. Our results suggest that projections of LUC or land values that do not incorporate market elements such as budget constraints and competitive bidding might produce incorrect policy recommendations. For example, an econometric hedonic value of open space, derived using only spatial and transaction data, might provide a biased estimate of the market values of open space. Policy recommendations based on decision-support tools might also fail to achieve intended goals should they neglect regional and local market and geographic conditions such as residents’ preference for OSA versus PUC and their perception of neighborhoods for land quality evaluation. For a hypothetical and homogeneous landscape, LUXE can trace the rate and location of land development over time under different market situations characterized by market levels. This tracing capability could be presented to decision makers for a better understanding of LUC pattern with given economic dynamics. Additionally, an extension of LUXE currently under development is able to explore the combined effects of LMs, landscape heterogeneity, and policies of environmental taxes and subsidies on the spatial patterns and extent of LUC, land rent, and ecological services.

The robustness of such assertions depends, of course, on the extent to which our results, derived using a simple, stylized model, are robust to alternative and more detailed model specifications. In that light, we acknowledge again several limitations of our model and suggest possible extension for further exploration. First, the model could be expanded to explore polycentric landscapes, docking to baseline analytical models such as Filatova, van der Veen, and Parker (2009). Second, alternatives to the CD utility function could be explored to evaluate sensitivity to the land decision-making algorithm. Different neighborhood definitions, including multiscale neighborhood perceptions and interactions, could also be added. LUXE currently has no mesoscale agent perceptions or cross-scale neighborhood interactions. Neighborhood amenities are perceived at a local scale, and market conditions are essentially perceived at a city scale, as agents are assumed to sample the entire landscape. The model could be extended to contain multiscale neighborhood definitions and agent perceptions, with feedbacks between neighborhoods (Torrens and Benenson 2005; Torrens 2006).

In additional to relaxing these simplifying assumptions, future research could develop in several directions. First, additional components like land investment and speculation, resale, and credit availability could be added to the market model. Second, empirically informed strategies on location and price decision making are required to accurately represent the real-world LMs and to be able to support policymakers. Third, as an example of an ABM of LUC, our model does not yet represent the whole process of converting agricultural land to inhabited homes. Incorporating developers and homebuilders is a work in progress. Finally, although our methods of analysis have revealed many salient patterns in the simulated data, more advanced methods of analysis and visualization could further enhance our understanding of the effects of various market representations on the LUC projections.

References


Irwin, E., and J. Geoghegan. 2001. Theory, data, methods: Developing spatially explicit economic models of land


Appendix

Constant and Household Level Parameters (Table 3)

Six constant parameters (Group I) are tightly related to the modeled land markets. To make a symmetric landscape and avoid geometric artifacts, we set the landscape size as 49 by 49 and the number of RHAs as 400. The number of 400 was large enough to generate outputs that support statistical examination. It was also small relative to landscape size and therefore prevented edge effects in spatial pattern measures. The proximity preference parameter was bounded by a range of 0.2 to avoid anomalies. Budget splitting factor was set as 0.6 and can allocate about 30 percent to 70 percent of budget to housing in most cases (values depend on land utility). Transport cost was set as one per cell unit. We bounded the values of Group II.a parameter to only include what we determined were economically or spatially relevant cases. Mean budget levels were 120, 140, 160, 180, and 200. With a standard deviation of 50 and budget splitting factor of 0.6, these budget levels created a diverse population of RHAs that had WTP above and below sellers’ WTA (100 in the case of budget constraints). Similarly, we implemented preference levels of 0.2, 0.5, and 0.8 to represent RHAs who, on average, favored OSAs over PUC, the two equally, and PUC over OSAs. These variations in budget and preference values well characterized agent heterogeneity.

Spatial Outcome Metrics

First, we used the maximum and average transport cost ($C_{\text{trans}}$) as two simple indicators of the overall size and distribution of the developed area. The transport cost is proportional to the Euclidean distance to the urban center. The maximum of transport cost is an approximate measure of the extent of the simulated monocentric, near-symmetric land development pattern. Average transport cost, taking both the quantity of LUC and their relative distances to the urban center into consideration, roughly measures the overall intensity of spread of the developed landscape.

Second, six standard spatial pattern measures were used to describe different aspects of the simulated landscape patterns.

1. Landscape shape index (LSI) is calculated as the ratio of total length of edges ($E$) to the minimum length of edges when the developed parcels are hypothetically rearranged to be the most compact (McGarigal et al. 2002). LSI is positively correlated with sprawl and fragmentation.

\[
LSI = \frac{E}{\min E}
\]

2. Fractal dimension ($d_f$), a metric that is empirically demonstrated to describe important differences in human-related landscape features (Batty and Longley 1986; O’Neill et al. 1988; White and Engelen 1993; Torrens 2008), is used to measure how self-similar development patterns fill the space.

\[
d_f = \frac{2 \times \ln(0.25 \times \text{perimeter})}{\ln(\text{area})}
\]

3. Edge density ($\rho_e$) is the average linear distance of edges ($e^i$) for all cells of the converted land (McGarigal et al. 2002; Parker and Meretsky 2004). It generally rises with increasing fragmentation.

\[
\rho_e = \frac{\sum_{i=1}^{n} e^i}{n}
\]

4. Aggregation index (AI) is calculated as the ratio of total number of adjacencies among developed land parcels to the maximum number of possible adjacencies (He, DeZonia, and Mladenoff 2000).

\[
AI = \frac{G}{\max G}
\]

5. Contiguity index (CI) examines the spatial connectedness between developed land parcels using a moving window (Ripple, Bradshaw, and Spies...
A parcel that is more connected to its neighbors defined by this moving window has a higher contiguity measure. Aggregation and contiguity indexes are positively correlated with compactness and negatively correlated with fragmentation.

\[
CI = \frac{\sum_{i=1}^{n} c_i - n}{12 \cdot n}
\]

6. Centrality index (CTI) depicts the concentration of developed land uses around the landscape center (Galster et al. 2001). If CTI is relatively large, it means that most developed land parcels are around the urban center, implying a relatively dense development pattern. It is defined as follows, where \( R \) is the radius of the landscape and \( \min(R) \) is the minimum radius possible given the amount of development.

\[
CTI = \frac{\min(R)}{R}
\]

Although these standard global fragmentation measures are able to quantitatively measure different aspects of the pattern of sprawl and fragmentation, one drawback of these global metrics is that the complex effects of landscape size and quantity of LUC are not accounted for (Saura and Martinez-Millan 2001; Wu 2004). This issue is particularly problematic for some metrics, including LSI, AI, and CTI. To help mitigate such problems, we normalized the quantity of change among experimental cases by halting the simulation once a minimum amount of LUC occurs, which is the minimum amount that occurs under each of the four market-level parameter settings. For example, if L2 produced the minimum number, say 150, of land-use conversions under a specific set of parameters, all other three levels of simulations were halted once 150 cells are converted. At this point we calculated quantity-controlled landscape metrics \( AI^q, LSF^q, \) and \( CI^q \).

Additionally, we revised the standard edge density by considering both quantity of LUC and distances to the urban center, creating a quantity-controlled and distance-weighted edge density (\( \rho_e^q \)):

\[
\rho_e^q = \frac{\sum_{i=1}^{q} e_i \cdot d_i}{q}
\]

These quantity-controlled metrics not only excluded the confounding impacts of landscape size and land change quantity, allowing us to compare the spatial pattern holding \( Q \) constant, but also shed light on the path of the modeled land-use changes, as they allowed us to compare development between experiments at the same stage of LUC.

To intuitively illustrate how these measures map to landscape patterns, we calculated measures for six representative landscapes (A–F) from our simulation (Table 5 and Figure 2). These representative cases show several characteristics. First, some of these measures have the exact same trend between cases. For example, both maximum and average transport cost sort the six cases in the order of \( C < D < A < B < E < F \) and fractal dimension and edge density in the order \( C < D < E < B < F < A \). As a result, we can group different metrics that produce the same orders into a single category to simplify our presentation. Second, these groups of metrics reveal different aspects or dimensions of the spatial pattern of the simulated landscapes. In other words, the complexity of spatial patterns cannot be simply depicted by a single metric or a single group of metrics; instead, it has to be examined from multiple angles. Nevertheless, taken together, these metrics provide a rich and comprehensive set of benchmarks to compare spatial patterns generated by LUXE with different market representations.