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An Agent-Based Model of Coupled Housing and Land Markets

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Abstract: This paper describes a spatially disaggregated, economic agent-based model of urban land use that includes explicitly specified and coupled land and housing markets. The three types of agents—consumer, farmer and developer—all make decisions based on underlying economic principles, and heterogeneity of both individuals and the landscape is represented. The model can be used to simulate the conversion of farmland to housing development over time, through the actions of the agents in the land and housing markets. Land and building structures in the housing bundle are treated explicitly, so the model can represent the effects of land and housing prices on housing density over time. We use the model to simulate the dynamics of land use changes as a representative suburban area grows. The presence of agent and landscape heterogeneity, stochastic processes, and path-dependence require multiple model runs, and the expression of spatial dispersion of housing types, overall housing density, and land prices over time in terms of the most likely, or 'average', patterns. We find that the model captures well both the general tendency for diminishing population density at greater distances from the center city, and dispersed leapfrog patterns of development evident in most suburban areas of the U.S.

Keywords: Land-use; Agent-based modeling; Land markets; Housing markets; Coupled markets.

1. Introduction

Concerns over urban sprawl have led many state and local governments in the United States to institute land-use control policies to slow or halt land conversion. Many of these policies, have been ineffective however, and may even have unintentionally caused further development [Grimm et. al., 2008; Irwin and Bockstael, 2002]. The failure is primarily due to a limited understanding of or capacity to manage the forces that drive urban land-use change. Land-use patterns are the result of complex interactions among biophysical components of the natural landscape, economic activities endogenous and exogenous to urban land-use systems, and human decision-making processes, which all can span multiple spatial and temporal scales.

Developing a model that captures these features of land use is difficult. One recent approach that appears to show promise is agent-based modeling. Agent-based models (ABMs) capture the activities and decisions made by multiple heterogeneous agents and explicitly include agent-agent and agent-environment interactions. Land-use ABMs offer several advantages over traditional planning and economic land-use models because they can explicitly model the spatial, path-dependent dynamics that characterize development patterns.

Most ABMs fail to incorporate key economic features. Filatova et. al. [2009] and earlier papers [Filatova et. al., 2007; Parker and Filatova, 2008] present the fullest, economically-based implementation of an agent-based land market to date. The authors have formulated a bilateral agent-based land market that explicitly models differences between a buyer's and seller's willingness to pay and willingness to accept, respectively, and the resulting bid and asking prices that form the final transaction land price [Parker and Filatova, 2008]. The authors are then able to exogenously specify different market power scenarios and explore the resulting spatial structure of rents and the division of gains from trade. However, their model lacks a housing market and cannot capture the feedbacks between land and housing markets that influence spatial rent structures and housing density.

Comment [NM1]: 1. Reviewer: "The paper explains a model of 'what' authors developed. It might be good to mention also for 'what for' it is going to be used, and which research questions it is supposed to answer."

Response: We have re-worked the paragraph below to express our underlying research questions.

This paper advances the ABM literature by explicitly incorporating a housing market with decentralized, bilateral transactions between heterogeneous agents to determine spatially explicit housing rents. We then use the model to investigate the feedbacks that emerge from fully coupled land and housing markets, and how those feedbacks influence the transitional dynamics and density patterns of development. We explicitly model the conversion of farmland to development, including the location and the density (i.e. lot size) of that development, and housing size. The model can provide a useful tool for analyzing the impacts of a variety of land use policy instruments such as minimum lot size restrictions (see Magliocca et al, 2009), impact fees, and purchase of development rights. Section 2 details our model structure, agent decision-making processes, and market interactions. Section 3 shows some results from model simulations. Section 4 concludes with a discussion of model capabilities and limitations and directions for future research.

2. Model Description

2.1 Model Structure

The model represents a growing exurban area in which land is converted from farming to residential housing over time. Farmers compare the returns from farming to expected profit from selling their land to developers. Farmers differ in how they form expectations about future prices of their land, and they adapt those expectations according to the success of past predictions. Farmers interact with developers in the land market. Developers determine the profitability of different types of housing that vary by both structure and lot size. Developers sell a housing good (i.e. a combination of a given house and lot size) to consumers who are differentiated by both income and preferences over different housing types. The model tracks development over time incorporating elements of path dependence and stochastic uncertainty that determine spatial development. A schematic of agent decision-making and market interactions is shown in Figure 1.

Comment [NM2]: 2. Reviewer: "It will be very useful to have either some kind of time sequence diagram or a verbal description of the sequence of events in modeled housing and land markets in 1 place (I see only elements of this description scattered around section 2.1)."

Response: We added a new figure showing the sequence of agent and market interactions within one time period, and dynamic, endogenous processes of consumers, farmers, and the developer.

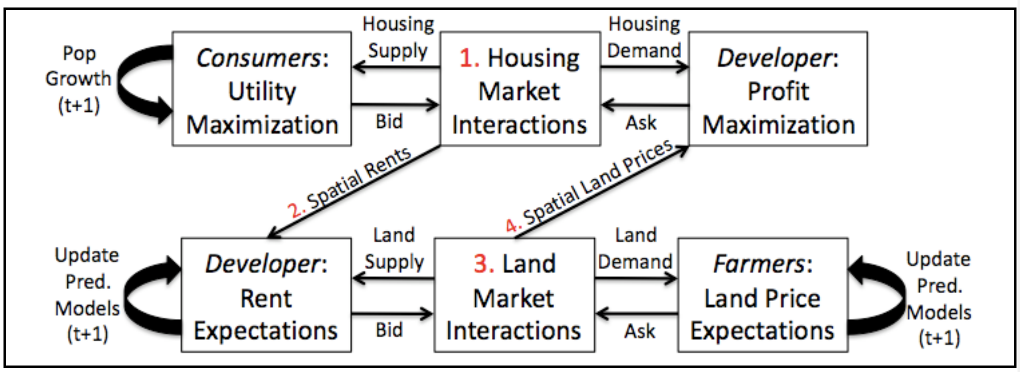


Figure 1. Conceptual map of agent interactions through coupled housing and land markets. The red numbers indicate the (counter-clockwise) sequence of events within one simulated time period (t). Agents (*italics)* are labeled with the underlying conceptual model that governs their behavior. Inter-temporal processes (t+1) shown include updating developer's rent prediction models, updating the farmers' land price prediction models, and exogenous growth of the consumer population.

2.2 Description of Model Agents

2.2.1 Consumer Utility, Willingness-to-Pay (WTP), and Willingness-to-Bid (WTB)

Each consumer c gets utility from a general consumption good and a housing good; a housing good can be considered a 'bundle' of one of eighteen different housing types, which are distinguished by different combinations of three different house sizes (h) and six different lot sizes (l). The utility of consumer c takes the standard Cobb-Douglas form:

(1) $$U(c,n) = \left(I_c - P_{ask|n} - \psi_n\right)^{\alpha_c} h_n^{\beta_c} l_n^{\gamma_c}\ ;$$

where I_c is income, ψ_n is the travel cost from the location of house n to the CBD, β_c and γ_c are the consumer's idiosyncratic preferences for house and lot sizes, respectively, and α_c is the preference for the non-housing consumption good. $P_{ask|n}$ is the developer's asking price for house n (see below).

We determine the utility for each of H_n existing or newly built houses for each consumer. The choice with the maximum utility for each consumer is defined as U^*. Holding U^* constant for all housing options facing each consumer, the R^* rent that would produce the same utility as the consumer's most preferred choice (i.e. an optimal rent such that the consumer would be indifferent between housing options) is calculated for each housing option. The difference between the rent being asked by the developer, $P_{ask|n}$, and the optimal rent, R^*, is used to form a WTB for each house.

(2) $$WTB(c,n) = WTP(c,n) - \left(P_{ask|n} - R^*(c,n)\right);$$

It is important to note that each WTB varies based on the consumer's income and idiosyncratic preferences for house and lot sizes. Thus, the full heterogeneity of consumer preferences is captured, and bids reflect the relative utility of each housing option offered.

2.2.2 Developer's Rent and Return Projections and Willingness-to-Pay (WTP) for Land

Developers make rent projections for every type of housing in every undeveloped cell based on distance from the established city, associated travel costs, and relevant local and regional rent information. If the housing type for which a projection is being made *is present* locally, the projected rent is the weighted combination of distance-weighted average rents from local and regional housing of the same type. In some cases, the housing type for which a projection is being made *is not present* locally. For these housing types, the rent projection is made based on regional rental information if it is available, or on average utilities of consumers occupying similar housing types if no other information exists.

Based on projected rents, potential returns are calculated for every housing type in every undeveloped cell by subtracting the costs of construction and infrastructure, which vary by housing type, and the price of land for the given cell. The maximum return for each cell is calculated as the maximum return over all possible housing types for the given cell. Maximum returns are then projected onto the gridded landscape to be used by the developer to determine the type and location of housing construction that maximizes profit across all vacant holdings.

The projected rent associated with the housing type that produces the maximum return in each cell i of farm F is specified as $R_{max|i}$. The developer's WTP for a given farm F is the average $R_{max|I}$ over the extent of the farm.

(3) $$WTP(F,t) = \frac{\sum_{j=F_i} R_{\max|j}}{A_F}$$; where A_F is the total acreage of farm F.

2.2.3 Formation of Farmer's Willingness-to-Accept (WTA)

Farmer expectations of land prices are formed using a randomly allocated set of twenty prediction models. Each prediction model uses one of six different methods for forming predictions based on up to ten years of past land prices from which to extrapolate next period's price expectation [Magliocca et al., 2009]. A farmer's decision to sell to a developer or continue farming is based on the expected return from selling his farm relative to the value of the farm's agricultural return per acre in perpetuity. The farmer's WTA is set to the greater of the two values. This enables the farmer to capture speculative gains from sale of his land when development pressure is high, while enforcing rational threshold below which the farmer would be better-off farming.

Comment [NM3]: 3. Reviewer: "Authors mention that farmers form expectations about future prices of their land. This is one of the most interesting parts of the model. However, it is not explained in the paper. It will be good if authors add an equation and/or 1-2 sentences explain this mechanism (for example in section 3.2.3)."

Response: We included a brief description of the predictions models here. Due to space constraints, our description must be limited. A more detailed description is available in the cited paper, and a full description of the prediction models will be presented in the appendix to a paper to be submitted shortly.

2.3 The Land Market

Following Parker and Filatova [2008], we use information on acreage demanded by the developer and supplied by farmers to define a "market power" parameter, ε:

$$\varepsilon = \frac{\left(d_{Land} - A_{F^*}\right)}{\left(d_{Land} + A_{F^*}\right)}; \qquad (4)$$

where d_{Land} is the acreage demanded by the developer and A_{F^*} is the acreage supplied by participating farmers. F^* is the subset of all farmers for which the developer's WTP is greater than or equal to the farmer's WTA. If the developer demands more land than farmers supply, ε is positive and farmers bid above their WTA. If farmers supply more land than is demanded by developers, ε is negative and the developer will bid below his initial WTP. However, neither the farmer/developer will bid below/above his WTA/WTP, respectively. Both farmers and developers adjust their ask/bid prices from their WTA/WTP to maximize gains from trade. If the bid from the developer is exceeded by the farmer's asking price, then the transaction is cancelled and the farmer returns to the farmer pool. Market power is dynamic because the amount of land supplied by farmers depends on the initial WTP of developers. The developer's WTP for a given farm depends on the level of rents in the housing market. Thus, the housing and land markets are explicitly linked.

2.4 The Housing Market

The developer and consumers interact in the housing market, determining the type of houses purchased and the rents in each period in each location, as shown in Figure 1. Houses enter the housing market in each period as either new construction or as pre-existing, recently vacated houses. For existing housing (H_{old}), the asking price is the expected rent associated with the location. For newly constructed houses, the asking price equals the developer's projected rent in the location of the newly constructed house, H_{new}.

Similar to the market power concept in the land market, we define a housing market competition factor, *HMC*, which describes the competition for housing each consumer faces in the housing market.

$$HMC_c = \frac{\left(NC_{H_c} - NH_{H_c}\right)}{\left(NC_{H_c} + NH_{H_c}\right)}; \qquad (5)$$

NH_{Hc} is the number of houses in the subset (H_c) of all existing houses that consumer *c* will bid on, and NC_{Hc} is the number of other consumers bidding on the subset of houses H_c. The subset of houses that consumer *c* will bid on, H_c, is defined as the subset of all vacant houses for which consumer *c*'s willingness to bid is greater than or equal to the asking price multiplied by the bid level for a particular housing type. The bid level is the average percentage that local sale prices for the same housing type were above/below the original asking price.

After *HMC* is observed, a consumer sets his bid in relation to the asking price of each house in the subset H_c in response to market conditions.

$$P_{bid}(c, H_c) = R^*(c, H_c) + HMC_c\left[WTB(c, H_c) - R^*(c, H_c)\right]; \qquad (6)$$

If HMC_c is positive, competition for housing for consumer *c* is high and the bid price will be set above the asking price. If HMC_c, is negative, competition for housing for consumer *c* is low and the bid will be set below the asking price. The adjustment of a consumer's bid price in response to market conditions allows the consumer to try to simultaneously maximize their gains from trade and the likelihood that they will be the highest bidder.

After the bidding process is completed, the highest bidder on each house is identified. Since consumers bid on multiple houses, it is possible that some consumers are the highest bidders on multiple houses while other consumers are not the highest bidder on any house. We thus match consumers that possess at least one 'winning bid' with the house that gives them the highest utility. The consumer's winning bid is recorded as the transaction price. The market is cleared by repeating this matching process with each of the remaining bids (which are kept constant) until all consumers are matched, all houses are occupied, or all positive bids are exhausted.

3. Model Experiments

The model was created using MATLAB programming language. Simulations were run on an 80x80 gridded landscape with each cell representing an acre for a total region of 6,400 acres, or 10 square miles. The CBD was set in the middle of the top row at coordinates (1,40) with an established developed area shown as the dark blue half-moon at the top of Figure 2. Initial development consists of randomly placed housing types 1 through 12 (see Table 1). Fifty farms surround the initial development and are shown as different colored patches in Figure 2. Initially, 334 consumers participate in the housing market, and an exogenous population growth rate of 10 percent a year is assumed. Incomes of incoming households are assumed to vary from $20,000 for the lowest quintile to $200,000 for the highest quintile.[1] Travel costs for households are assumed to depend both on time and monetary costs. Time costs are assumed to be $1.30/mile[2] and monetary costs are $0.54/mile (BTS, 2007). As new households move to the region, they demand housing; a single developer for the region responds by buying land from farmers and building houses. Thus, farmland is gradually converted to developed uses over time.

Comment [NM4]: 6. Reviewer: "Could you please provide a reference for travel costs data ($1.30/mile, and $0.54/mile)?"

Response: Please see citation and accompanying footnote.

The model was run 30 times with the same set of experimental parameters, and each run tracks growth over a 20-year period (model years 11 through 30, with the first 10 years used for prediction model calibration). Farmers' locations and agricultural returns were held constant across all runs. The distribution and location of housing types in the initial city were also held constant across all runs. Draws from income and consumer preference distributions and the initial assignment of all prediction models (i.e. for land and housing price predictions and distance discounting) were allowed to vary randomly across each of the 30 runs. Holding landscape features constant across runs eliminates sources of geographic variability, while exploring the effects of path-dependence and stochastic processes on development patterns.

Table 1 provides a description of housing and lot sizes associated with each housing type, and summary statistics across 30 model runs. Even though the landscape was held constant across runs, the housing types built across runs showed a good deal of variation. This variation reflected the importance of heterogeneity in consumer demand. The most frequently developed housing types were those with small or medium sized houses on 1- and 2-acre lots, which were affordable for most consumers. No 5-acre lots were built over the entire period, but there were likely to be some 10-acre lots. The absence of 5-acre lots was due to the combined effects of high construction costs relative to expected rents, and the wealthiest consumers opting for houses on 10-acre lots.

Stochastic elements in the model (i.e. random draws from consumer income and preference distributions and assignment of prediction models) limit the insight of any single model realization. Instead, maps of the most likely, or 'average', development patterns were constructed (Fig. 3a-d). For each time step displayed, the development pattern consists only of cells that were developed in at least 60 percent of runs and approximates the average percent area developed observed across all 30 runs. Within each of those cells, the housing type with the highest probability of occurrence is mapped. Thus, we can reconstruct the most likely location and density of development.

[1] These data were based on median household incomes for suburban counties in the Mid-Atlantic region (Delaware, Maryland, Pennsylvania, and Virginia) from the 2000 Census.

[2] We assumed time costs to be a function of average road speed (30 mph), average number of workers per house (2), average wage per person ($30/hour), value of time as a percent of wage (50%), and the road network indirectness coefficient (0.3) (this is the ratio of network distance to the Euclidian distance).

Table 1. Number of lots by type of house/lot combination, at t=30.

Housing Type	Lot Size (acres)	Housing Type Description	Mean Number of Lots	Std. Dev.	Mean Annual Rents (2007 $)	Std. Dev.
1	**¼ ac lots**	Small house	96	12	8,899.29	482.79
2		Medium house	58	46	12,186.06	1,022,20
3		Large house	128	74	15,119.46	1,006.69
4	**½ ac lots**	Small house	175	113	10,097.02	1,069.66
5		Medium house	180	124	13,204.93	1,129.09
6		Large house	172	74	16,692.85	889.26
7	**1 ac lots**	Small house	506	120	12,675.49	497.69
8		Medium house	220	88	15,471.26	621.07
9		Large house	163	68	19,595.76	676.23
10	**2 ac lots**	Small house	589	104	19,794.96	575.73
11		Medium house	375	92	21,823.79	544.95
12		Large house	141	34	25,719.98	976.22
13	**5 ac lots**	Small house	0	0	0	0
14		Medium house	0	0	0	0
15		Large house	0	0	0	0
16	**10 ac lots**	Small house	40	32	33,008.27	4,228.99
17		Medium house	36	29	35,303.91	3,889.41
18		Large house	8	12	34,579.29	7,626.81

The model also allowed us to capture the time path of development. Farmland was increasingly converted to development as demand for housing grew. By 30 years out, about 60% of the land area is developed. However, development spread in a dispersed, or 'leapfrog', manner. This is a result of both spatially heterogeneous agricultural productivity and heterogeneity in how farmers formed expectations about future prices. Early development occurred at distant locations because land prices were relatively low and farmers in these areas sold first. Later, development filled-in closer to the initially developed area, due to rising land prices (Fig. 4) and increasing development pressure (Figs. 3b and 3c) close to the initial 'city'.

Another evident trend was the decrease in the average density as distance from the CBD increased. As population and consequent demand for housing increased, prices for land close to existing development also increased (Fig. 5) over time. Concurrently, increased rents enabled the developer to bid more on land close to existing development, but the developer was also constrained by profit-maximization to develop 2-acre or smaller lots (Fig. 3b and 3c). As time progressed, large lots became relatively scarce and demand for them grew. Given the level of expected rent for large lots and decreasing land prices with distance from the CBD, new construction becomes more likely far from the CBD in the last 5 years of simulation (Fig. 3d). The observed density gradient and increasing trend in land prices over time indicate that this ABM can reproduce trends expected by urban economic theory [Irwin, 2009] (Fig.4).

4. Discussion and Conclusions

In this paper, we described an ABM of urban growth and land-use that integrates microeconomic fundamentals into a framework capable of capturing full heterogeneity and spatially explicit development patterns. At this point in the model's development, we are most interested in the qualitative behaviors that emerge from explicitly coupling housing and land markets.

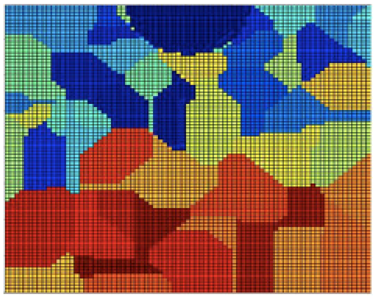
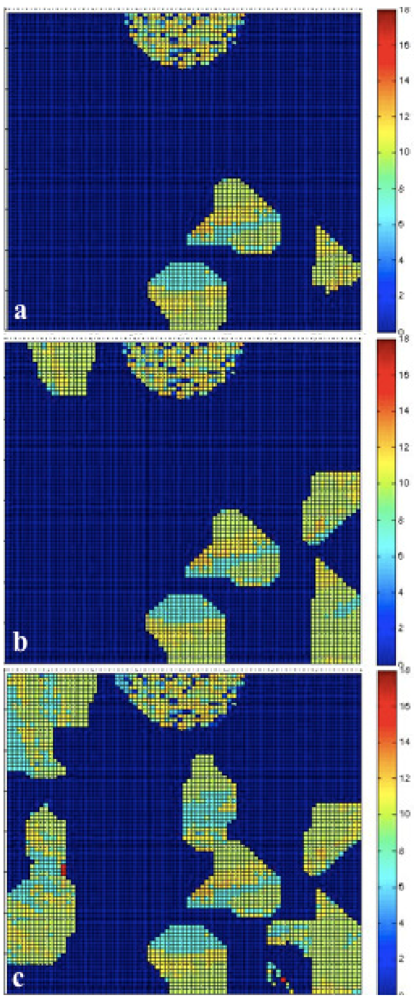


Fig. 2. Initial landscape configuration.



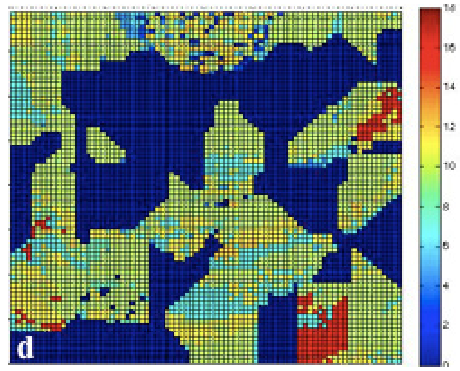


Figure 3: ‘Average’ development pattern maps for time steps a) 15, b) 20, c) 25, and d) 30. Housing types are color-coded from 1 (dark blue) to 18 (dark red).

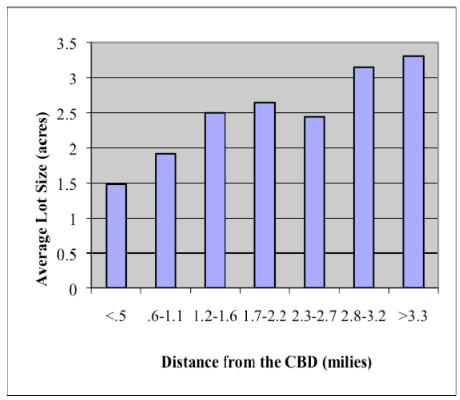


Figure 4: Mean lot size by distance from CBD, at 30 years.

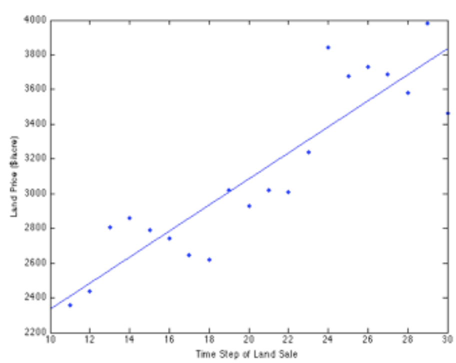


Figure 5: Mean land price ($/acre) at each time step. Ordinary least squares line (R^2 value of 0.8133) indicates an increasing trend in land prices over time.

Our results demonstrate the effects of this coupling. We observe how housing demands from heterogeneous consumers can drive up rents for particular housing types and/or in particular locations. The developer reacts by increasing his willingness to pay for land in those locations, which is then countered by reactive farmers increasing their asking prices. The interplay between markets and agents' heterogeneous preferences and perceptions results in a dispersed, 'leapfrog' development pattern (Fig. 3) that is consistent with what we observe in actual practice. In addition the model also reproduces the general trends in land prices and land uses over time predicted by economic theory (Figs 4 and 5).

Although our results are promising, there is a need for further testing of model sensitivities and outcomes. Advances in methods for testing ABMs have been made such as pattern-oriented modeling [Grimm et. al., 2005] and the 'invariant-variant' method [Brown et. al., 2005] and will be applied to this model in future work. In addition, the current version is simulated on a featureless plain. Proximity-based environmental amenities are not represented, which have been shown to significantly influence development patterns [Filatova et. al., 2009; Irwin and Bockstael, 2002; Wu and Plantinga, 2003]. Future model iterations will incorporate proximity-based amenities to explore their effects on development patterns. The model can be used to assess a range of policy options for achieving land use goals. We plan to assess a range of policies for preserving land from development, for protecting environmental resources from the effects of development, and for increasing infill and higher density development.

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References

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

Bureau of Transportation Statistics (2007). "Average Cost of Owning and Operating an Automobilea (Assuming 15,000 Vehicle-Miles per Year". Research and Innovative Technology Administration. Available at: www.bts.gov/publications/national_transportation_statistics/html/table_03_14.html

Filatova, T., Parker, D.C., and van derVeen, A., Agent-based urban land markets: Agent's pricing behavior, land prices and urban land use change, *Journal of Artificial Societies and Social Simulation*, 12(13), 2009: http://jasss.soc.surrey.ac.uk/12/1/3.html.

Filatova, T., Parker, D.C., and van derVeen, A., Agent-based land markets: Heterogeneous agents, land prices, and urban land use change, *Proceedings of the 4th Conference of the European Social Simulation Associations* (ESSA'07), Toulouse, France, 2007.

Grimm, N. Faeth, S., Golubiewski, N., Redman, C., Wu, J., Bai, X., and Briggs, J., Global Change and the Ecology of Cities, *Science*, 319, 756-760, 2008.

Grimm, V., Revilla, E., Berger, U., Jeltsch, F., Mooij, W.M., Railsback, S., Thulke, H., Wiener, J., Wiegand, T., and DeAngelis, D., Pattern-oriented modeling of agent-based complex systems: lessons from ecology, *Science*, 310 (5750), 987-991, 2005.

Irwin, E., New Directions for Urban Economic Models of Land Use Change: Incorporating Spatial Heterogeneity and Transitional Dynamics, Presented at Journal of Regional Science 50th Anniversary Symposium,Federal Reserve Bank of New York, April 23-24, 2009.

Irwin, E. and Bockstael, N., Interacting agents, spatial externalities, and the evolution of residential land use patterns, *Journal of Economic Geography*, 2: 31-54, 2002.

Magliocca,N., McConnell, V., Safirova, E., , and Walls, M. An Economic Urban Growth Model with Agent-based Housing and Land Markets" Paper presented at 56th Meetings of the North American Regional Science Association International, San Francisco, California, November 2009

Parker, D.C. and Filatova, T., A conceptual design for a bilateral agent-based land market with heterogeneous economic agents, *Computers, Environment and Urban Systems*, 32, 454-463, 2008.

Wu, J. and Plantinga, A.J., The influence of public open space of urban spatial structure, *Journal of Environmental Economics and Management*, 46(2), 288-309, 2003.