Polyspatial Agents for Multi-Scale Urban Simulation and Regional Policy Analysis

Abstract

For some time, simulation has been used for policy experimentation with complex urban-regional systems. However, serious difficulties exist in faithfully modeling such systems across scales. Fundamentally new simulation architectures may be required to address conventional policy, for which cross-scale complexities present a challenge. We introduce a new modeling approach for modeling urban-regional systems from the bottom-up and the top-down, using polyspatial computational agents that are capable of functioning and adapting flexibly across scales, allowing a greater range of questions to be posed in simulation. We prove the usefulness of this approach in evaluating policy scenarios.

Keywords: multi-agent systems, geosimulation, scale, regional science, complexity.

Introduction

Geography is an important consideration in designing, applying, and examining the influence of public policy (White 1972), but a fundamental difficulty often exists in connecting policies across scales from the local to regional (Abdel-Rahman and Anas 2004). Calls to reconcile the two date to the 1970s (Coppock 1974) and some contend that little progress has been made since then (Macleod and Goodwin 1999). One might also consider a more extreme case of the argument: that policy would benefit from connecting the *individual* to the regional. Again, this was recognized decades ago (Hägerstrand 1970), but remains a concern (Miller 2007). It is our contention that progress *could* be achieved in aligning local, urban, and regional public policy with the help of *geographically-informed urban simulation*.

While simulation may perhaps seem to be an unlikely catalyst, it is significant. Simulation has emerged as an important approach to experimentation with plans, ideas, and hypotheses that cannot feasibly be studied in their natural contexts. However, the sorts of methodologies traditionally developed for policy analysis in geography—which largely follow regional science—are in some respects outmoded relative to conventional ideas and theory: there is a need for new approaches and tools that are extensible enough to adapt as our knowledge and policies evolve. This may require methods that represent a significant leap from the existing state-of-the-art.

In this paper, we will demonstrate exactly these sorts of tools, which although nascent in their development, show significant promise in better representing regional-scale urbanization in a more realistic fashion and greater flexibility relative to shifting policy concerns that require local behavior and phenomena to be traced through to regional consequences, and in reverse for regional policy to be translated to the grassroots. Our methods are based on agent-based modeling and geosimulation that work from the bottom-up, but they can also be docked with traditional methods from regional science to consider regions from the top-down. Importantly, they are *polyspatial*, capable of handling spatial processes flexibly as needed, with the advantage that they permit multi-scaling in simulation and treatment of the messy complexity in between. Our approach embodies a novel departure from traditional regional science modeling, ultimately extending the range of questions that can be posed in simulation and broadening the relevance and versatility of simulation in policy development and analysis. We will demonstrate the usefulness of the scheme with application to a range of policy-relevant scenarios, which consider diverse scales and include a wide cast of synthetic urban processes, actors, and agency.

Background

The challenge in relating urban and intra-urban geography to regional policy is not to be understated. Colloquially put: the whole (the region) is often different than the sum of its parts (cities) (Portugali 2000) and for urban simulation, methods developed at the scale of the region may not hold relevance at local scales or may not reconcile across scales. In short, we may need tools designed specifically to study the (micro-level) parts of regions and their interactive dynamics, but this has not traditionally been the remit of regional science, which has understandably busied itself with a holistic outlook.

The complexity that shapes the relationship between processes across scales is sometimes a formidable barrier to reconciling geographies, because of the unwieldy influence of feedback, path dependency, phase shifts, bifurcation, self-organization, emergence, and other properties that render it difficult to chart trajectories from the local to the regional (Batty 2005). Although attempts have been made to do so (Sonis and Hewings 1998), many existing regional science models are ill-equipped to treat complexity.

Complicating matters, the very nature of interaction within urban systems has radically transformed in recent decades with the result that there has been a fundamental shift in the way that many processes manifest across scale (Malecki and Gorman 2001). The implications for traditional urban models are significant: long-useful methods predicated on distance and distance-decay, such as the spatial interaction model, are not as relevant as they used to be. Attempts to reenergize classic approaches, through consideration of entropy in urban gravity models (Wilson 2010), for example, have done little to resolve the problem, because the very nature of how systems work has changed. Models and even underlying theory in traditional approaches may simply not be flexible enough to adapt to novelty while the world changes.

Moreover, urban and regional planning and public policy has undergone a general shift from top-down styles of management and analysis to now include grassroots concerns, from the bottom-up (Lester *et al.* 1987). As a result, the primacy of the region in policy concerns has, to some extent, been diluted and there is now parallel interest in the link between local-level policy and regional outcomes (Sabatier 1986).

The introduction and proliferation of micro-simulation provided regional science's main response to these challenges (Clarke 1996) and micro-simulation soon found its way into urban models (Wegener and Spiekermann 1996). The California Urban Futures (CUF) models, developed by Landis (2001) and colleagues, and Urbansim, developed by Waddell (2002) and colleagues are recent examples. Both introduced significant advances over traditional regional science approaches, particularly in the resolution of their spatial detail and the fidelity of the economics that they incorporated. More traditional popular models, in the vein of the DRAM/EMPAL models developed by Putman (1979), by comparison, used coarse geography and were relatively abstract in their description of urban phenomena and the data input to them.

While particularly innovative when first introduced, micro-simulation does have some limitations for urban simulation. In particular, it is strongly *data-oriented*, relying on statistical inference to index rather than represent *behavior* and *phenomena*. Further, micro-simulation is largely linear in its consideration of interaction and static (at best using comparative statics over longitudinal time-frames) in its treatment of dynamics. These traits limit the ability of models to introduce *novelty*—new urban forms, new urban phenomena, new behaviors that might emerge—in simulation. This could artificially constrain the ability of the models to support policy experimentation, narrowing the focus of the model to questions that match the underlying economic rationalization or assumptions of the model and limiting answers to those that can be polled from the data that the model consumes. For many applications, this is sufficient (perhaps even desired), but for policy with tendrils that reach into issues of complexity, alternative schemes may be required.

Very recently, the use of automata-based models has emerged in response to these concerns. Automata are simple processing units that facilitate interaction by coupling transition rules, states, space (as a localized geography of interacting automata), and time. They commonly appear in urban simulation as cellular automata (arranged in a regular lattice), agent automata (also known as individual-based models, where states and rules are formulated to ascribe life-like agency to the processing), or multi-agent systems (where many agents are allowed to interact). Automata-based models offer the advantage of being able to focus on massively-interactive dynamics with great computational efficiency and explorative flexibility. They also allow developers of urban models to craft simulations that treat large populations of urban entities at individual scale (Benenson and Torrens 2004). However, the introduction of automata to urban simulation has mostly occured with abstract representation of urban phenomena and piecemeal attention to the range of urban processes considered. Many automata models have been developed as academic tools to think with and this is symptomatic of their nascence in use but also stems from more fundamental concerns, regarding a lack of theory for complex urban systems, limited availability of software and template modeling architectures, and short supply of urban data at fine resolutions (Torrens and O'Sullivan 2001). The SLEUTH model developed by Clarke and colleagues (Clarke *et al.* 2007) and the SIMPOP models developed by Sanders, Pumain, and colleagues (Sanders *et al.* 1997) exemplify this abstract, but massively dynamic approach, which although very useful and innovative is difficult to reconcile with policy-testing, because of its relative simplicity in representing urban processes. The MOLAND and MURBANDY cellular automata models originally developed by Engelen, White, Uljee, and colleagues (Engelen *et al.* 1995; White *et al.* 1997; Engelen *et al.* 2002) are something of an exception, as they have been targeted for operational planning support and they have enjoyed widespread application across European cities. However, they are based on cellular automata as the underlying processing mechanism, which ascribes proxy behaviors to cells in simulation as pattern-based envelopes for urban phenomena, rather than introducing realistic behavioral agency.

Automata use in urban simulation stands in stark contrast to that in transportation modeling, where automata are employed with relative success in engaging with theory (Balmer *et al.* 2009) and policy (Nagel *et al.* 1999). Granted, transport systems and phenomena are more well-understood and tractable than other urban phenomena because they are confined to fixed conduits and conform to traffic laws and convenient physics of space and time, but it would be useful for policy if we could reach the same level of integration between urban automata models, theory, and outcomes that transportation research enjoys. This would require a modeling and analysis pipeline that treats regional urban processes and patterns at multiple scales, working from the top-down with compatibility to existing regional science, but also treating the grassroots of urban systems from the bottom-up, in a massively dynamic and flexible setting, with all of the urban complexity that entails.

This is what we introduce in the remaining sections. Although the pipeline that we will present is not completely integrated and it does not deal exhaustively with urban processes, it does demonstrate how such a modeling infrastructure can be built and we will illustrate the usefulness of the approach with respect to policy concerns.

Methods: building dynamic, scaling city-regional systems in simulation

In essence, we will present a new pipeline for urban simulation and policy analysis with attention to the regional and local scale and consideration of the processes that connect their interstitial dynamics.

Our goal in developing a new simulation pipeline was to treat urban processes at their characteristic resolution and space with behaviors appropriate for a given scale. We also enabled hierarchical nesting between different scales and resolutions to facilitate interactivity from the individual, through the neighborhood and the intra- and inter-urban scale, to the region, with process dynamics that run from the top-down and the bottom-up. In this sense, we can consider the automata that we develop as being *polyspatial*, i.e., as having malleability to function across scales and to adapt to serve the model with appropriate behaviors and dynamics for the spatial context that they find themselves in and the geographical information that they are exposed to and that they process. Computationally, we formulated our automata as geographic automata, which are a hybrid of traditional automata and Geographic Information Science that allow interoperability between cellular automata and agent-automata (Torrens and Benenson 2005). Our modeling approach is also designed to flexibly dock with existing schemes or models from regional science.

Generating cities from the top-down: from the macro-scale to the meso-scale

At their heart automata models are fundamentally information-processors and can take on many roles. We will refer to them as automata when discussing their computational nature and as agents when they are used to represent substantive urban actors or processes. First, we will describe how the model can function at regional–to–intra-urban scales, from the top-down. Then, we will discuss how the model works from the household-to-neighborhood level, in the opposite direction in terms of process dynamics, which are considered from the bottom-up.

We begin the simulation pipeline holistically at regional-level, with a top-down input-output model (Isard 1998) and this shows how the pipeline supports docking with existing regional science methods. A volume (D_{city}) or rate (Δ_{city}) of population growth or decline is associated with a particular city in a simulated urban-regional system, per time-step t and the population variable (P) is considered as being sourced exogenously from the system. It is also possible that these data could come from some other source or model (a stock-and-flow model, for example); our framework is agnostic in this way. We are only concerned with intra-system dynamics in this example, however, so we ignore the intellectual origins of change and we follow its trajectory once it enters the system. Inputs are formally collated as follows.

$$P_{city}(t+1) = P_{city}(t) + \begin{cases} \Delta_{city}\text{, or} \\ D_{city} \end{cases}\text{, where } D_{city} \text{ can be derived from } \left(P_{city}(t)\Delta_{city}\right) \qquad \text{(i)}$$

Above, P_{city} represents the population total for a particular city gateway ($city_1, city_2, \dots, city_n$).

This parameterization of P_{city} anchors the trajectory of the system's population in space and time and can be used to establish seed sites in the simulated city-system, or to experiment with alternative formulations of initial settlement geography. This formulation is synonymous with Nineteenth Century urbanization in North America, organized around gateway cities (Hall 1988). It also allies with theory regarding the roles of cities as "growth poles" (Darwent 1969) in regional system development. The actual volumes or rates for population infusions were derived from historical census data in the examples that we will show, so that growth and decline were allied to real-world conditions. But, these data could alternatively be fed to the model by the user (yum, yum).

From the meso-scale to the macro-scale: generating cities from the neighborhood-up

Once exogenously-derived growth enters into the system form the top-down, it is converted to heterogeneous agents that may then be subjected to local processes, local context, and local information (Figure 1). In this way, we represent bottom-up (inter-*urban* and *intra*-urban) as well as top-down dynamics. We are primarily interested in the urban geography of the city-system and so we introduce geographic processes that explain the distribution, space-time trajectories, movement, and spatial context of urbanization that develops at meso-to-micro–scales. This is close to the domain of micro-simulation, but our scheme begins to depart significantly from the bid-rent and assignment procedures traditional to micro-simulation *as we approach finer resolutions*. In micro-simulation, the model usually retains the same form, regardless of the scale of data input to it. However, in our approach, we treat local-scale *process models* as distinct from those that operate at coarser scales, but we retain the capability of information-exchange between scales by allowing the automata that we build to operate polyspatially.

[Figure 1 goes here.]

In being loose-coupled to the input from the model at macro-scale, any down-scale dynamics are naturally enveloped within a regional context. At intra-urban scales, automata are introduced as cellular parcels of land, which form a lattice of units that are considered for change in the simulated system, each cell representing an urban neighborhood. Many existing urban models use a similar mechanism for holding variables (pixels in CUF, parcels in Urbansim) but our model differs considerably because cells are dynamic information processors; they do not simply hold variables but have their own behavioral and process mechanics. Automata cells are also heterogeneous in their behavior at this scale and they encounter relatively unique geographic information as the simulated space evolves: this provides independent local context to the processes that act on and within them.

Our characterization on urbanization at the meso-scale is couched in population geography, but there is nothing preventing us from also considering environmental, economic, infrastructure, or political influences. Specifically, we approach population geography from the vantage of the *inter*active influence of demographics; intra-system migration; local diffusion across several cells; and the space-time trajectory of development and settlement, represented using movement regimes. *Within*-the-cell (i), crude (i.e., those that do not include migration) demographic dynamics are represented, using birth (b) and death (d) of population at the scale of an individual cell (i). We also consider emigration (em) and immigration (im) of population between cells. Endogenous, meso-scale, within-area demographic processes are coupled as follows.

$$\delta_i(t+1) = im(t) - em(t) + b(t) - d(t) \tag{ii}$$

These meso-scale drivers of population geography dynamics are then woven into the macro-scale (regional) process-pipeline as follows.

$$P_i(t+1) = P_i(t)\delta_i(t) \tag{iii}$$

Next, we need to account for the spatiotemporal dynamics that will enable these schemes to become *interactive* at meso-scale in simulation. We achieve this by modeling movement of people through the urban system over space and time. The geography of movement is a significant driver of urban change in its own right (Limtanakool *et al.* 2007), but we also use movement as a proxy dynamic for other economic, urban planning, policy, and cultural phenomena, so that the *rules* of movement are designed to match the *trajectories* of these mechanisms over urban space and time. In addition to movement, we use diffusion to enable the porous exchange of population between cells, to account for local spillover effects (Morrill

1968). The range of diffusion is specified within a local neighborhood filter, or area (A), as a dynamic interaction between a source cell (i) and sink cells $(j_1, j_2, \ldots, j_n)$, as follows.

$$P_j(t+1) = P_j(t) + \frac{P_i(t)}{A_i} - \frac{P_j(t)}{A_j} \qquad \text{(iv)}$$

In this particular case, we used expansion diffusion, but alternative schemes could be used to account for hierarchy, contagion, mixed approaches, etc. The diffusion range can also be tempered by distance-decay or attenuation ($\pm\alpha$, yielding A^{α}), where α may be monotonic or could act to index some known or hypothesized distribution.

Thus far, we have described locally interactive processes. Typically, in a cellular automata-type model, local processes would be permitted to interact by proximity through fixed-shape neighborhood filter (see Clarke *et al.* 1997, for example), as in our diffusion routine. Used in isolation, this may be sufficient to describe urbanization in cities of times past that had constrained physical transportation (White and Engelen 2000), but urban dynamics in modern cities are catalyzed by forces that enable action- and interaction-at-a-distance, because they are so functionally engaged with the regions in which they are situated (Brown and Holmes 1971). To enable these dynamics, we introduced *agent-based* movement schemes that can take the results of the local processes and animate them through space and time, over longer distances or matching spatiotemporal trajectories of urbanization processes. This is quite more flexible than the simple, regular neighborhood filters employed in urban cellular automata. Trajectories may have economic (Clawson 1962), social (Farley *et al.* 1978), or political (Carruthers 2003) *precursors*, but we are interested in their influence on the time geography of urbanization, so we treat their geography, i.e., their spatial patterning and dynamics. Of course, additional sub-models could be docked within this scheme to explain underlying economics, and so on. Variable movement schemes are introduced, with qualitatively distinct space-time mechanics. Again, this demonstrates the malleability possible in using polyspatial agents. Five movement schemes are considered, although the framework allows for others to be added. While the number of movement schemes is small, each movement procedure will encounter and consume a rich wealth of geographic information as it operates over the cellular lattice of the model, allowing for many possible outcomes.

In the model, movement operates as a rule (R_L) that manipulates the trajectory of population change by animating (i.e., advancing it in space and time) that change through variably-considered geographical neighborhoods ($N_i(t)$) of a source cell (i). In essence, each neighborhood serves as a spatiotemporal envelope within the evolving lattice-space of the simulated city-system and movement agency provides the engine for its dynamics, following whatever unique geographic information manifests (locally) at that geography. We impose no formal requirement for the neighborhood geography and we will demonstrate neighborhoods of different sizes and shapes in addition to network neighborhoods. The bundle of time denoted by $t \rightarrow t+1$ is malleable, allowing many movements to take place within the sub–space-time of a model's incremental counter, i.e., $t_0', t_1', \ldots, t_t' \in (t \rightarrow t+1)$. Consequently, many different characteristic timings of a process or entity can be treated simultaneously. The general framework is as follows, which can be parameterized to produce different heuristics.

$$R_L: \boldsymbol{L}(t) \rightarrow \boldsymbol{L}(t+1), \text{ where } L_0, L_1, \dots, L_n \in \boldsymbol{L} \tag{v}$$

Two movement schemes focus on very local change around a given cell. (Movement is applied to population around all cells in the simulated system.) *Immediate movement* enables change due to accretion (Batty 1991), so that R_L is executed within N_i as follows (Figure 2).

$$N_i(t \rightarrow t+1) = (i,j),(i+1,j),(i-1,j),(i,j+1),(i,j-1),(i+1,j-1),(i+1,j+1),(i-1,j-1),(i-1,j+1) \tag{vi}$$

[Figure 2 goes here.]

The *nearby movement* heuristic extends the spatiotemporal envelope to a Moore neighborhood of user-defined order, >1. This enables space-time change by infill (Vallance *et al.* 2005), as in transit-oriented urban design, for example (Cervero 1998).

The *irregular movement* heuristic is based on a correlated random walk within a local neighborhood around a source cell. At each cell traversed in the walk, a volume of population change is associated with the areas of the lattice that are visited. The heuristic is designed to produce urbanization as if constrained by natural barriers (Ward *et al.* 2000). The area (A_i) of the neighborhood within which the walk occurs is user-defined, as are the number of steps performed in the random walk, i.e., $|t \to t+1|$. In the examples that we will show, the neighborhood for interaction is related to the historical trajectory of the heuristic in simulation. Correlation in the trajectory of movement is achieved as follows.

$$N_i(t \to t+1) = random(i,j) \in \begin{Bmatrix} i,j(t) \\ ++i(t) \\ --i(t) \\ ++j(t) \\ --j(t) \end{Bmatrix} \qquad \text{(vii)}$$

The *leap-frog movement* heuristic also operates as a random walk within a user-defined neighborhood and time-frame. However, in this case, only the terminal location in the walk is considered for urbanization. This procedure mimics speculative development (Clawson 1962) of urbanization beyond existing sites (Benguigi *et al.* 2001).

The *road-building* movement heuristic uses the irregular movement scheme to establish seed sites (network nodes) in the simulated landscape. These are ascribed user-defined weights and the Roulette Wheel selection algorithm (Goldberg and Deb 1991) is then used to populate connecting strips of linear urbanization between seed nodes. Nodes are considered as neighbors for interaction and connections form as a network of links. This follows theories about urban linkage introduced decades ago (Whebell 1969; Hoyt 1964) that remain relevant, particularly in policy evaluation of the connections between transport and land-use (Handy 2005) and the merits of urban transport corridors (Cervero 1998). The heuristic is quite different than other road-building approaches used in urban simulation (Yamins *et al.* 2003), which often adopt a *general* fractal or geometric equation to build city-wide transport infrastructure. Our approach is *uniquely and heterogeneously* tied to local urbanization, which better matches the incremental development of cities and roads symbiotically over time.

It is important to note that as these heuristics establish new sites of urbanization, those newly-formed settlements can subsequently be expanded and modified—geographically—by the same rules operating in subsequent time steps: growth may beget more growth (or decline may catalyze further decline). This establishes the conditions for path-dependence through lock-in, momentum, and inertia that characterizes many cities (Batty 2008).

We also introduce a *meta-controller* that allows the user to manipulate (or even disengage) each movement heuristic. This can also be formulated as a finite state machine (Sipper 1997) that allows for different sequences of growth processes to interact at a high-level, governed by state transition rules.

Generating neighborhoods from the household-up: from the micro-scale to the meso-scale

Much of the innovation and complexity in city-systems is sourced from the individual citizens that inhabit urban spaces and that energize the urban substrate with their action, interactions, and activities. While it is implied, in the models just discussed, that the behavior of the population is driving the geography of urban dynamics, we have not yet treated that behavior *explicitly* in the model. We will now demonstrate a micro-model that treats the detailed interactions of households at a very local geography, focused within a single neighborhood of the previous model and down to the scale of individual properties and residents considered within a property submarket or social neighborhood. While reliant upon what happens holistically, the processes of urban dynamics at this scale may often be unique to that particular local context. We therefore need qualitatively different urban mechanics—and algorithms—to treat them. But, we also need them to interoperate with the entire information infrastructure that we have just described. Again, this proves the utility of a *polyspatial* model.

We used agent-based models to animate at-a-distance interactions between automata cells using geographic heuristics in the previous model and these heuristics were used as *proxy processes* for underlying behaviors. In our micro-to-meso model, we will use the agency of the agent-based approach to map *realistic behavioral agency* to agent-actors in the urban system. This is more akin to endowing the agents in the model with artificial intelligence, rather than the relatively straightforward information processing capabilities of automata that were leveraged in the previous example. We will also consider the urban fabric (spatial, built, economical, and social) in a lot more detail.

The coarser-scale representation of cities used in the previous model was appropriate to the characteristic spacing and timing of urban dynamics at that level of abstraction. However, as we move to the micro-scale and to the agency of individual households, we need a richer representation. Importantly, at the micro-to-meso–scale, households are proactive: they structure their activities in space and time to avail of opportunities that they encounter (or perceive) in the city. Rather than bending simply to a geographic process such as diffusion or an abstraction of their behavior such as nearby contagion, agents in the model are driven by realistic sociospatial and socioeconomic behaviors, with dedicated cognition of and preferences for urban structures and phenomena specific to those scales. The micro-modeling scheme is illustrated in Figure 3.

[Figure 3 goes here.]

At micro-scale, we characterize urbanization as the dynamics between households, preferences, properties, property attributes, social neighborhoods, property submarkets, and accessibility of amenities. We also consider influx and outflux of population to this scheme, commensurate with the movement dynamics described in the higher-level model.

Properties are ascribed prices (p) hedonically, as a bundle of attributes that potential occupants (or a market collective of individuals) value. This follows evidence from consumer studies that households use a bundled-value approach in comparing residential location choices (Rosen 1974).

$$p_j = C + \sum_{k=1}^{n} v_k Q_k, \text{ where } k = \{k_{real\ estate}, k_{neighborhood}\} \tag{viii}$$

Above, p refers to the price of a property j, C is a constant, n is the number of attributes considered hedonically, v is the hedonic value of the attribute, Q is the quantity of the attribute, and k is used to denote characteristics/attributes of the urban fabric, where $k_{property}$ and $k_{neighborhood}$ are the set of property/real estate unit and neighborhood attributes considered. For the examples we will show, we considered $k_{real\ estate}$ as containing housing type, housing size, and property accessibility; and $k_{neighborhood}$ as containing neighborhood accessibility, neighborhood economic status (value platform), and neighborhood ethnicity quotients. In both cases, additional criteria could be added to these indices; the framework is relatively agnostic in this regard.

Accessibility was considered to the downtown, nearest highway on-ramp, nearest shopping mall, and nearest grocery store; these values were calculated by road distance in a Geographic Information System (GIS). k-values were ascribed to real estate in the model using data from the U.S. Census Bureau summary files and county Tax Assessor's Office data.

We should mention that the characteristics of agents in the micro-model were updated on a temporal schedule that was different (but nested within) that of the regional model. Some of these characteristics (such as preferences) can shift quite quickly, while others (such as neighborhood conditions) may take longer to emerge. Timing and sequencing of update in the model is flexible, however, and the important point to make is that urban processes can be represented at their (different) characteristic time, in addition to their characteristic geography.

In endowing agents with behaviors, we considered householders and we did so in detail, including their heterogeneous preferences and information. We also considered other entities as automata: the larger real estate markets and social neighborhoods that agents inhabit and interact with. This establishes the proactive agency of simulated residents by endowing them with the ability to collect information (fully or partially) about their urban surroundings, to weigh it against their preferences (and this could establish bias), and to react to that information (Clark 1993). The overarching intent, here, is to treat the agency that drives the intra-urban movement introduced in the regional-level model, but with its characteristic timing and process mechanics at a micro-scale.

Preferences (l) were introduced to the model for real estate $l_{real\ estate}$ and neighborhoods $l_{neighborhood}$ and those preferences were parameterized to interact with the set of $k_{real\ estate}$ and $k_{neighborhood}$ characteristics already discussed; in this way, they provide an elasticity per-characteristic and per-household. In the example we will show, we assigned l-values to agent-households in the model synthetically. Alternatively, these could be specified using survey data, if available. To animate their preferences in the local geography that they perceive, households (u, w) first calculate their propensity for mobility (i.e., the trade-off between residential stress and resistance, informed by their *household* conditions and *neighborhood* surrounding; Pr_{stay}) and this determines whether they will stay in a given location (i, j) or whether they will move to a new location (Pr_{move}), where $Pr_{move} = \left(1 - Pr_{stay}\right)$ (Rossi 1955). This propensity is determined from the characteristics and preferences already discussed, chained as follows.

$$\forall\ u, Pr_{stay}(u, i) = \sum \left(k_{neighborhood} l_{neighborhood}\right) + \left(k_{real\ estate} l_{real\ estate}\right) \qquad \text{(ix)}$$

In this scheme, the l-variables provide elasticity for the k-characteristics, but on a *per-household* basis. Thresholds for moving were introduced to the model synthetically, but could come from real data if available.

If households decide to move in simulation, they engage in a nested, hierarchical search of available alternatives, driven by their (unique) preferences and (unique or shared) information about available options. This follows evidence of such behavior in American cities (Clark 1993). Households first evaluate all neighborhoods available to them at a particular location and time in simulation (using $k_{neighborhood}$) and if a neighborhood is deemed to be suitable for their preferences $l_{neighborhood}$, they will focus their search on properties within the neighborhood (using $k_{real\ estate}$), matching available options to their fine-scale preferences, $l_{real\ estate}$. The actual choice heuristic is made per household (u, w), per neighborhood, and per property (i, j), calculated as follows.

$$Pr_i(u) = \sum (l_{real\ estate} k_{real\ estate}) + \sum (l_{neighborhood} k_{neighborhood}) \tag{x}$$

In expanded form, the calculation for the real estate (property-level) component then reads as follows.

$$\sum(l_{real\ estate}k_{real\ estate}) = \begin{bmatrix} b_1\left(1-\left|k_{real\ estate_v}-k_{agent_{econ},u}\right|\right) \\ +b_2\left(k_{real\ estate_{single},j}l_{real\ estate_{single},u}+k_{real\ estate_{condo},j}l_{real\ estate_{condo},u}\right) \\ +b_3\left(1-\left|k_{real\ estate_{size},j}-l_{real\ estate_{size},u}\right|\right) \\ +b_4\sum\left(k_{real\ estate,access_{\begin{bmatrix} downtown \\ highway \\ mall \\ grocery \end{bmatrix}},j}\ l_{real\ estate,access_{\begin{bmatrix} downtown \\ highway \\ mall \\ grocery \end{bmatrix}},u}\right) \end{bmatrix} \quad \text{(xi)}$$

Above, $real\ estate_v$ denotes the price of a particular property unit, $agent_{econ,u},u$ is the economic status of a household (u), $k_{real\ estate_{single},j}$ is a dummy variable for single-family housing, $l_{real\ estate_{single},u}$ indicates household u's preference for single-family housing, $condo$ denotes a similar dummy for condominium units, $k_{real\ estate_{size},j}$ represents the size of a real estate unit j and the matching l-variable corresponds to household u's preference for size, $k_{real\ estate,access_{\begin{bmatrix} downtown \\ highway \\ mall \\ grocery \end{bmatrix}},j}$ denotes the accessibility of a particular real estate unit j to key amenities in the city and the matching l-variable specifies household u's preference for that accessibility. The b_m-variables are used as levers in simulation that allow the model user to weight each of these influences in simulation. They could also be derived empirically in a regression-type model.

The expanded form of the neighborhood/market-level calculation is as follows.

$$\sum(l_{neighborhood}\, k_{neighborhood}) = b_5(1 - |k_{neighborhood_{econ},j} - k_{agent_{econ},u}|) + b_6 k_{neighborhood_{ethnicity},j} \tag{xii}$$

Above, $k_{neighborhood_{econ},j}$ is the median economic status (property price) associated with the neighborhood that contains property j, and $k_{neighborhood_{ethnicity},j}$ is the neighborhood ethnicity quotient associated with property j. The b_m-variables are considered as previously discussed and all $m = 6$ of them sum to unity.

The ethnic mix of a neighborhood will adjust dynamically as households move into and out of the area as a simulation progresses. We specify price dynamics using vacancy as an index:

$$V_j(t+1) = V_j(t)\left(\frac{1 + R_{normal_{type}} - R_{type,z}(t) + \lambda\left(1 + R_{normal_{type}} - R_{type,z}(t)\right)}{1+\lambda}\right)^{\beta} \tag{xiii}$$

Above, V_j is the price of a property j, $R_{normal_{type}}$ is the normal vacancy rate for real estate of a given $type$ (condominium or single family housing), λ is a parameter for weighting system-wide influence, $R_{type,j}$ is the vacancy rate for real estate of a given type in neighborhood z, and β is a scaling parameter for the property price/value adjustment. As vacancies increase in a neighborhood, prices will adjust downwards (and the rate of price deceleration can be controlled by the user).

Policy experiments, performed *in silico*

In the following, we will describe two simulations run using the simulation pipeline already outlined. These simulations are designed to illustrate the usefulness of the scheme in supporting policy experimentation. In the first example, we used the regional-scale (urbanization and intra-urbanization) model to explore several scenarios about the evolving Midwestern Megalopolis. In this case, we produced regional-scale urbanization from the bottom-up mesoscopic dynamics that evolve at intra-urban geography within the simulated city-system. In the second example, we take a hypothetical neighborhood cell from that scenario and simulate the microscopic dynamics that generate intra-urban conditions, from the scale of individual households up to socio-spatial neighborhoods and real estate submarkets. Taken together, this establishes a framework for modeling regional-scale urbanization from the household to the megalopolis, or in the other direction (Figure 4).

[Figure 4 goes here.]

Evolving the greater Chicago metropolitan region from small building-blocks

In the one application of the simulation pipeline, we used the polyspatial scheme to generate synthetic urban dynamics for the greater Chicago metropolitan area (Table 1). We evolved the city-system in simulation for two hundred years from 1800 to 2000 as this represents the significant period over which its present-day spatial structure formed and this was also the longitudinal range for which we had reliable population data with which to calibrate the model. We designated the (present-day) larger cities in this system as seed sites for the top-down portion of the model as these represented the main sinks for immigration in the system. Historical census data for population were trickled into the model per-year in simulation (Figure 5), anchoring the potential population volume in simulation to realistic levels. However, the *geography* of where that population settled was determined by the model.

[Table 1 goes here.]

[Figure 5 goes here.]

As a base simulation scenario, the motion control heuristics were applied with equal propensity. Used in conjunction with calibrated population input, this was sufficient to generate realistic-looking patterns of urbanization and population density for the city-system (Figure 6). To test the goodness-of-fit to real-world conditions, we used patch-area fractal measurements (Riiters *et al.* 1995) to empirically determine the scaling of urban coverage across the city-system and across scales. (Admittedly, there are many possible other mechanisms for doing this.) Measures of the fractal dimension of the synthetic city (minimum of 1.516, maximum of 1.549, average of 1.523, with standard deviation of 0.011) are commensurate with those observed for other major U.S. city-systems (see Batty & Longley (1994), who calculated values of 1.4 to 1.7 in the United States, for example). This may be taken as implying that the configuration of the urban geography in the simulation scenario and population geography scales well relative to real-world allometry.

[Figure 6 goes here.]

Additionally, we altered the relative weighting of the motion controllers to produce urbanization under hypothetical, policy-based, what-if scenarios: for urban growth management, road-oriented urbanization, suburban sprawl, and polycentric urbanization. Our approach here was ad hoc: we assigned relative propensity for the heuristics to apply per cell (or at all) in simulation per time-step (Table 2, Figure 7). The 'true' amount of each process needed to generate a required outcome is not known *a priori* and so the exercise is relatively normative. This is actually quite a useful approach for policy because it enables the introduction of indexed *policy levers* as goals that might factor into consideration in planning and managing regional urbanization. In essence, macro-scale regional-level outcomes are achieved by manipulating the geographic engines of urbanization, growth, and decline at meso-scale, through bottom-up (and top-down) evolution of the city-systems dynamics.

[Table 2 goes here.]

[Figure 7 goes here.]

In summary, the results from this application of the simulation pipeline show that the polyspatial scheme can successfully manage simulation of urbanization that mimics the holistic patterning and timing of urban development in the real-world. Moreover, by playing with the mechanics of urbanization, one can explore different policy outcomes. In each of the parameterizations that we explored, connections exist between dynamics in simulation and debate in the literature. In short, the simulation pipeline has diagnostic value. Growth management can be produced by focusing road-building, limiting leapfrogging and speculative development on the urban fringe, and promoting compact development through local infill (Song and Knaap 2004). However, unconstrained road-building and leapfrogging can foster urban sprawl (Ewing 1997). This can be reined in through polycentricity if efforts are made to localize urbanization between growth poles (Gordon and Richardson 1997) (Figure 7).

Building socio-spatial neighborhoods and real estate submarkets from household dynamics

In the next scenario, we used the micro-model to simulate *detailed*, *behaviorally-driven* urban dynamics within a single cellular unit of the larger urbanization model previously described. There is a richer level of output from this scale, so we will describe the results of these scenarios in more detail than those generated by the regional model.

At the micro-scale, we were interested in the interplay between household residential preference, relocation behavior, neighborhood-level social dynamics, and real estate sub-market dynamics. We built a set of synthetic neighborhoods/sub-markets (2.78 km^2 in area), composed of 375 properties (condominiums and single-family homes) and 350 households as seed conditions. Realistic household and property attributes were ascribed to the synthetic urban area using County Assessor's Office and U.S. Census Bureau's Summary File data. We should stress that we considered only a single urban 'cell' from the regional model. The cell is therefore arbitrary in the geography of the regional-level model, but it represents a realistic micro-sample of a real-world neighborhood. Properties were geocoded in the simulation using real parcel geometries chosen arbitrarily from a U.S. city. The area was divided into three distinct property markets (Figure 8), with the addition of a fourth, newly-built market considered in one of the scenarios (Table 3). The model was run in simulation for five hundred time-steps (equivalent to forty years of urban dynamics in the regional model). The temporal resolution is therefore finer than that of the regional model, because the pace of change at neighborhood scale is faster.

[Figure 8 goes here]

[Table 3 goes here]

Four scenarios were simulated in the model. By altering the parameters of the model as policy levers, we were able to produce a rich set of micro-to-meso urban dynamics in simulation, representing socio-spatial segregation, boom and bust cycles in property markets, heterogeneous socio-economic neighborhoods, gentrification, and residential displacement.

The first scenario was a straightforward *extrapolation of the seed conditions* into the future. We assumed an initial household growth rate of 3% of the initial household population and normal (sub-market–wide) vacancy rates for real estate were set at 15% (these rates can then change locally within the simulated space as households move in and out). Input new households seeking homes were seeded with artificial, mixed state descriptors and preferences. (More realistic preference data could be introduced from surveys or polls, for example, if available.) The second scenario considered the influence of *increased demand* on the dynamics of the area: a greater number of potential buyers were input to the simulation, each with high economic status (three times higher than the base scenario, with higher implied purchasing power and higher expectations for neighborhood value platform). The third scenario was used to simulate the effect of *increasing the supply of real estate* in the simulated space, by adding additional real estate development at a high property value (market 4 in Table 3). The fourth scenario combined the second and fourth scenarios, to produce *both increased demand and increased supply*.

Extrapolation from the base scenario

Under the extrapolation scenario, the three property submarkets largely retained their original distinctions over time, with minor volatility (Table 4). The total household population remained relatively stable, even though the initial household growth rate was set to 3%. At each time-step, a certain number of immigrating households (determined by household growth) was input to the simulation (as in the regional model). However, not all of them purchased properties. Their decision-making depended on local context and their own unique preferences and for many of them none of the markets were a good fit. Also, a natural rate of death was considered (again, as in the within-cell demography characterized in the regional model), which offsets growth. Economic status also remained distinct: Markets 1 and 2 remained lower-income and Market 3 stayed high-income, on average. (As a reminder: initial pre-simulation market characteristics are summarized in Table 3.)

Property values increased throughout the simulation, but markets retained their relative value-platforms, although volatility was high and at times there was short-lived price parity between markets. Throughout the simulation, there was marked negative correlation between values in Markets 1 (which originally had a low value-platform) and 3 (which originally had a high value-platform), which suggests some competition between the two for pricing.

However, there *was* some marked divergence in ethnicity-profiles between markets. Market 1 grew less diverse, while Markets 2 and 3 retained their ethnic profiles. Neighborhood-wide, there was almost complete ethnic separation by the end of the simulation, although the effect was gradual. This suggests some socio-spatial separation in neighborhood dynamics. Over the course of the forty-year run, the original resident profiles in all markets declined, with 25-30% of the original residents remaining by the end of the simulation.

Essentially, the extrapolation scenario produced *socio-spatial separation without socioeconomic separation*. The dynamics were quite subtle, but the end result was dramatic. The effect was generated using minor initial heterogeneity and gradually accelerated through the influx of slightly different residents to the neighborhood that traded-off their individual preferences for neighborhood-level attributes. This allies with Sakoda's (1971) and Schelling's (1971) classic experiments on paper and checkerboards, but reached the same results with a much richer behavioral foundation and a more flexible simulation environment. Clearly, this is valuable as a tool for testing policy that might concern neighborhood social geography or individual and collective perceptions and behavior.

[Table 4 goes here.]

Increased demand scenario

Under the demand scenario, economic status increased throughout the simulated space. The increase was particularly dramatic in Market 3: the affluent market became even more affluent, with a growth of 70% in economic status for much of the simulation. Market 2, which originally had a relatively low economic profile also became wealthier, by 40%. Ethnic diversity remained relatively stable across markets. There was a lot of volatility in property values and there was moderate fluctuation in total household counts. The number of original residents dropped to 20% in most markets after forty years in the simulation, but Market 1 retained 45% of its original population.

The policy lesson in this scenario is that, *in the absence of controls, demand-side economics can transform the geographical balance of a neighborhood with just small changes in individual behavior*, leading to marked differences in economic geography at a coarser scale. In essence, this is indicative of herding behavior in collective action (Surowiecki 2004).

Increased supply scenario

For the supply scenario, we added an additional fourth market to the space. This had little influence on economic status, which remained relatively flat. However, the total household count across all markets became highly volatile. Property values were also volatile for the first 20 years of the simulation, with swings of $\pm$30%, but these fluctuations leveled-off in the second half of the simulation. Overall, property values increased substantially across the simulated space. Ethnic diversity remained stable, except in Market 1. Originally, Market 1 was diverse, but by the end it steadily lost diversity, becoming 80% Latino by the end of the simulation.

The outcome, in this scenario, is that *increasing supply alone produces incredible volatility and variability in neighborhood geography*. This follows theories in urban geography, which suggest that the addition of public housing can in some instances concentrate poverty and catalyze residential segregation by impacting ambient property markets (Holloway *et al.* 1998; Rosenbaum 1995). In our scenario, the economics of the entire area increased, although there was widespread variability.

Increased supply and demand scenario

The supply-demand scenario produces different outcomes again. There was a lot of volatility in the count of total households in the simulated space (Figure 9), with fluctuations of $\pm$15% and relatively little stasis over the forty year period. The ethnic geography also changed remarkably: Market 1, which was initially diverse, became completely Latino. Market 1 was originally low in its value platform and economic status relative to the other markets, and this remained the case. The economic status of the entire area increased, but remarkably so in Market 3. This market was originally the most affluent and it grew increasingly so over the course of the simulation. Property values also increased throughout the area, but again increases were remarkably high in Market 3. The area retained more original residents than the base scenario: the decline was by 60% to 70%.

The end result, in this scenario, was *neighborhood gentrification* (Glass 1964). Interestingly, urban geographers have had difficulty in the past in explaining gentrification dynamics from purely supply-side (liberal, humanistic) or demand-side (production, Marxist) explanations (Hamnett 1991, 1992); this experiment suggests that a combined approach may provide paths to reconcile the two debates.

[Figure 9 goes here]

Conclusions

Computer models are useful tools for exploring the connection between urban and regional systems and policies that might traverse between scales. However, cities and regions are adapting and evolving in novel ways and the fundamental connections within them are also changing and urban simulation has been slow to adapt to the changing needs of policy. Updating these methods is something of an imperative. Policy often needs a focus on local elements of regional systems from the bottom-up and their connection to coarser-scale phenomena, while also appreciating the role of top-down policy and process. In addition, policy must often consider dynamics in addition to statics and it must grapple with massive interactivity and connectivity across scale. Moreover, policy often needs to consider the role of complexity in governing the trajectories of urban-regional processes. We would benefit from a next generation of models that could flexibly adapt to these shifting demands. This may require a fundamentally new architecture for simulation.

In this paper, we have demonstrated a novel simulation pipeline that can generate regional forms and processes from the bottom-up, while also entertaining top-down methods. This is enabled by the use of polyspatial agents that can, essentially, become different models at different scales, with ability to metamorphosize and adapt flexibly to simulation applications and to diverse information streams supplied to them in simulation.

The advantages of the scheme are numerous. Of paramount importance given the shifting nature of policy concerns is that the modeling approach is inherently flexible. Automata are, fundamentally, basic processing units with tremendous extensibility. In using automata as a foundation, our pipeline can support a variety of urban processes and we have demonstrated many: diffusion, leapfrog development, action-at-a-distance, action-by-proximity, demographic change, residential location and relocation, development, socio-spatial segregation, the collaborative dynamics of preference and choice, accessibility, geographical inertia, gentrification, herding, and so on. The model also supports an almost limitless potential for introducing agency and actors. Indeed, agents may be characterized polymorphically and polyspatially, within one pipeline, as urban processes, homeowners, developers, relocating households, social neighborhoods, property markets, land parcels, real estate units, and so on. The model can also flexibly scale in spacing (and timing), from regions of city-systems to individual households. Although we did not go into detail in our description, we have shown in passing that our modeling framework can be connected rather seamlessly to spatial analysis, statistical analysis, GIS and spatial databases, and visualization, in addition to a variety of urban and regional theory. This is important, as many of these connections are to tools that are commonly used in policy research (Munger 2006). Although not discussed here, we have also enabled the modeling scheme to function over high-performance computing, allowing for simulations to be run with massive amounts of interacting agents, and run for a huge array of parameterizations and variables. The scheme can also be docked with existing models, regardless of whether they operate from the top-down or the bottom-up. In this way, it is agnostic with respect to the direction of urban processes or the legacy of related simulation schemes that one might wish to connect with.

The overarching advantage of the scheme that we presented is that it does not constrain the range of questions that could be posed in simulation. This stands in contrast to traditional approaches, which often impose a relatively limiting theoretical or methodological frame on models, and by extension on policy considerations in simulation. Indeed, we demonstrated how our scheme may be used to explore policy scenarios relating to urban growth management, socio-spatial segregation, and the behavioral foundations of demand and supply economics in property markets. It is worth emphasizing again that we supported this within a *single* modeling framework.

There are many things that our model does not include and clearly it is a blueprint for future work. Although we did attempt some validation, we largely skirted the issue of verifying simulation scenarios. This is an issue that we are actively pursuing, but it is not the main focus of this paper. The purpose of our simulation scenarios was to prove the usefulness of the scheme, generally, rather than to work as a support system for particular policies, so validation is perhaps less relevant in this case. Validation is an inevitably thorny issue for such models because data are almost always in short supply or partial in their coverage of the many varied systems that one would like to consider. Also, any dynamic model that speculates in what-if scenarios may not be suitable as a forecasting tool and so measures of goodness-of-fit are perhaps less appropriate than in classical statistical models that deal in statics and probability under strict assumptions. Moreover, city-regions may well generate completely novel behaviors that have no analog in our current understanding (the recent foreclosure crisis is a recent example) (see Batty and Torrens 2005 for a lengthy discussion of these issues). Our approach does, however, open-up opportunities for validating models at different scales if validation is possible or feasible and, more importantly, it also facilitates tracking of the space-time trajectories of phenomena, individual households, and perhaps even policies, across scales. In this way, the parameter-space of a simulation can be followed as different policy levers are pulled in the model.

Another shortcoming of our model is that it is not completely integrated as simulation software; it runs as self-contained modules per model, although it does move across scales seamlessly in its treatment of theory. We considered only one intra-urban 'cell' in the regional model when clearly we would need to represent many millions to account for the dynamics of an entire regional system at this scale. Realistically, dedicated intra-urban and inter-urban residential relocation models and property development models would be required to populate the movement heuristics of the regional model from the bottom-up. We have developed these models separately and integration is an ongoing topic of research that we are pursuing. To build a model at the scale of individual households for an entire Megalopolitan region would be a huge undertaking, given the diversity of context and historical precedent that would need to be considered. At least conceptually, though, this is possible with sufficient effort.

Perhaps one more criticism is that many important urban processes and systems are not considered in the model we presented. Realistically, the list of things that might be considered as 'missing' is almost endless and those that do appear represent the bias of the model-builders, rather than suggesting any fundamental limitation of the approach. Obviously, in many areas, there are parallel developments in agent-based modeling that could be allied: in economics (Tesfatsion 2002), land-cover change research (Manson and Evans 2007), sociology (Epstein 2006), political science (Macy and Willer 2002), transportation (Nagel *et al.* 1999), and so on. Our intention, in this paper, was to detail a pipeline that could provide a scaffold for future improvements. The significant point that we would like to highlight is that we have enabled an indelible path to be traced from micro-to-macro scale and back again by facilitating the representation and simulation of varied, but related, urban phenomena at different geographies within the region. This dramatically improves the usefulness of models in supporting emerging policy concerns and fundamentally expands the range and depth of questioning and exploration that can be performed in simulation. These sorts of schemes may even be future-proof, a condition that is rare in policy research.

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Tables

Table 1. The cities considered in the urbanization model, and their present-day populations.			
Illinois	*Indiana*	*Michigan*	*Wisconsin*
Chicago*, 2,851,268	South Bend*, 104,215	Grand Rapids*, 193,710	Milwaukee*, 605,013
Aurora, 172,950	Gary*, 95,707	Lansing*, 113, 802	Madison*, 235,419
Rockford, 157,280	* Denotes that the city was used as a seed site for the top-down model.		
Joliet, 147,648			
Naperville, 143,661			

Table 2. The relative weighting of motion controllers that generated different urbanization processes in simulation.	
Goal	*Relative weighting*
Urban growth management	• Road-building, irregular; • Minimal leapfrogging; • Nearby, immediate, diffusion with small range to promote infill
Polycentric urbanization	• Immediate > nearby; • Leapfrog; road-building; irregular; • Diffusion with small range
Suburban sprawl	• High leapfrogging to promote fringe development; • High road-building; • Irregular; • Nearby, immediate, diffusion with small range to catalyze new development
Road-oriented urbanization	• Immediate, nearby; • High road-building

Table 3. The initial conditions for the micro-model.				
	Market 1	Market 2	Market 3	Market 4
Households	99	107	96	48
Diversity	55% non-Latino	30% non-Latino	5% non-Latino	5% non-Latino
$\bar{x}$ *economic status*	0.23	0.2	0.35	0.33
Average housing type	Mixed	Mixed	Mostly condominium	Mixed
Average square feet	0.27	0.26	0.13	0.26
$\bar{x}$ *property value*	0.24	0.24	0.42	0.42
$\bar{x}$ *access downtown*	0.16	0.46	0.52	0.35
$\bar{x}$ *access mall*	0.25	0.25	0.79	0.36
$\bar{x}$ *access highway*	0.71	0.48	0.54	0.35
$\bar{x}$ *access grocery store*	0.52	0.14	0.2	0.41
Initial normal vacancy rates and household growth were set per-scenario. Fractions are normalized values.				

Table 4. Summary of the results of simulation scenarios for the micro-model (the supply and demand scenario is illustrated in Figure 9, and so we did not represent it here)

	Base scenario	**Demand-driven scenario**	**Supply-driven scenario**
Total households	Stable	±10% change	±5% change
Economic status	Stable	Huge increase in some markets, but not others	Stable
Original resident profile	80% decline	55% to 80% decline	60% to 70% decline
Ethnic diversity	Complete separation	Stable	Loss of diversity in one market
Property value	60% to 80% increase with huge early volatility	Distinct results (flat, steady increase, huge volatility) in different markets	20% to 30% increases; huge early volatility

Figures

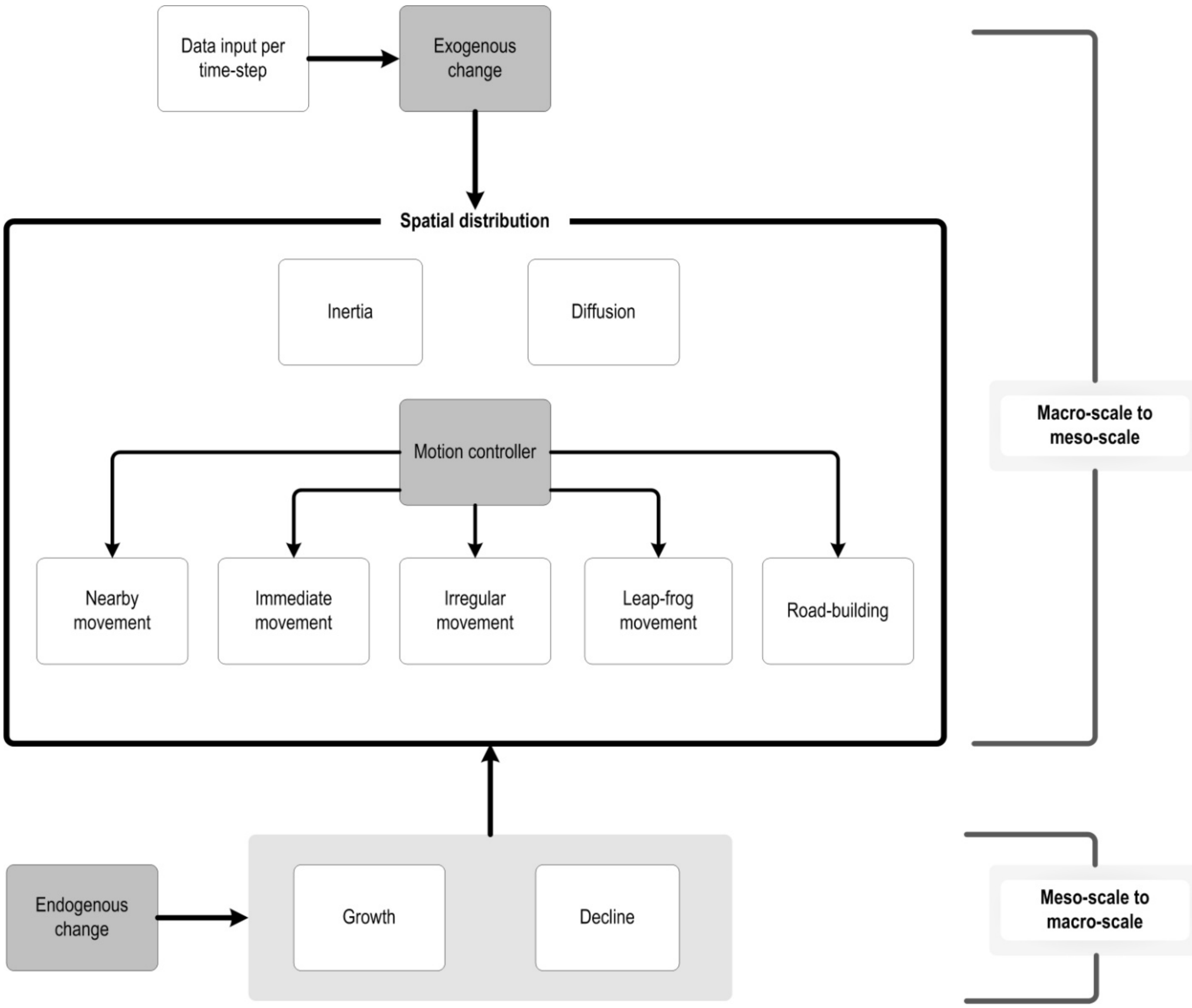

Figure 1. The programmatic flow of information in the macro-model.

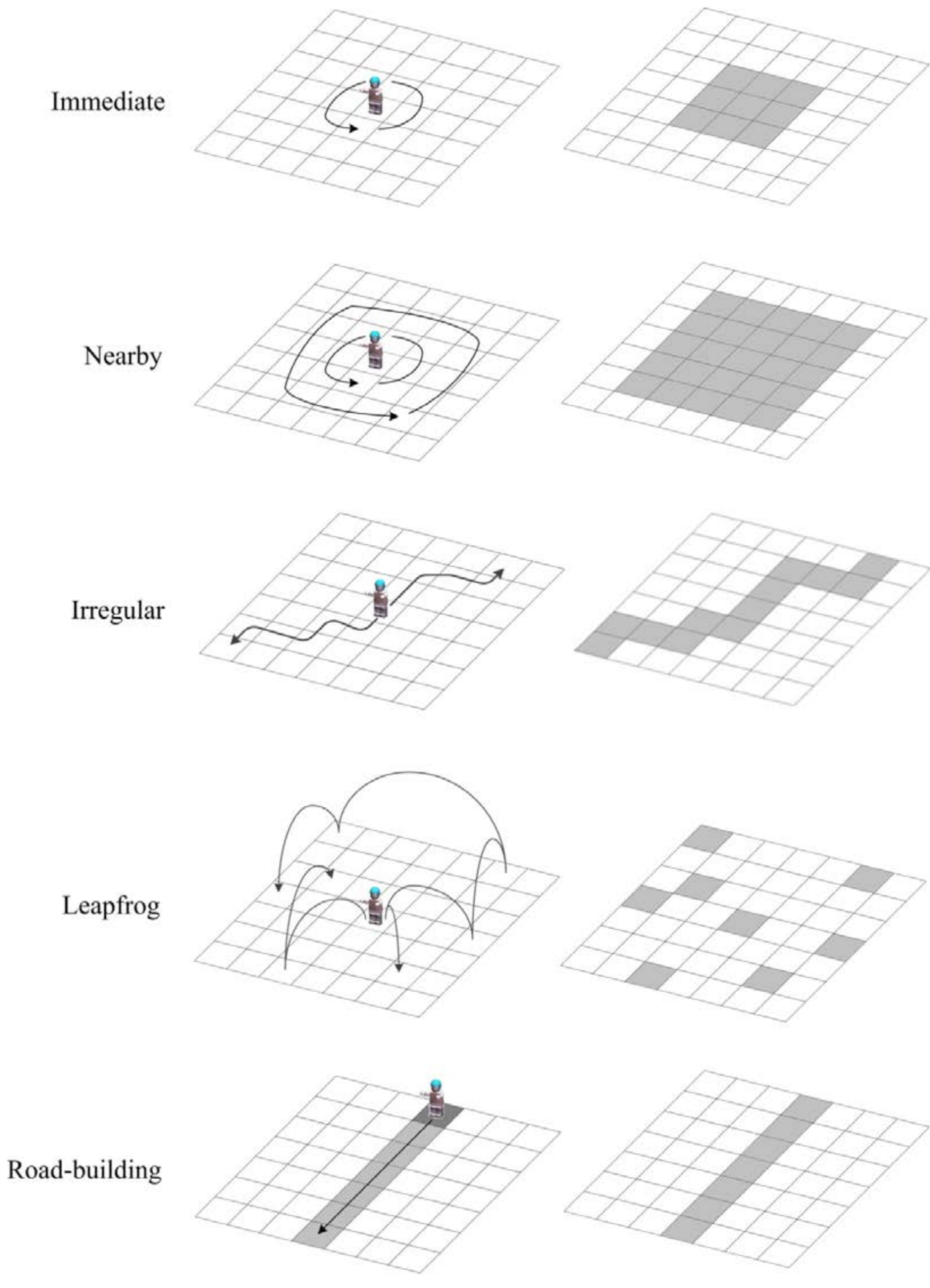

Figure 2. The five movement heuristics used in the model to animate urbanization along space-time trajectories (left-hand side) and the types of patterns that they produce in idealized conditions (right-hand side). These heuristics may operate individually under the specification of the model-user, or they may be structured together as a finite state machine, under the guidance of transition rules.

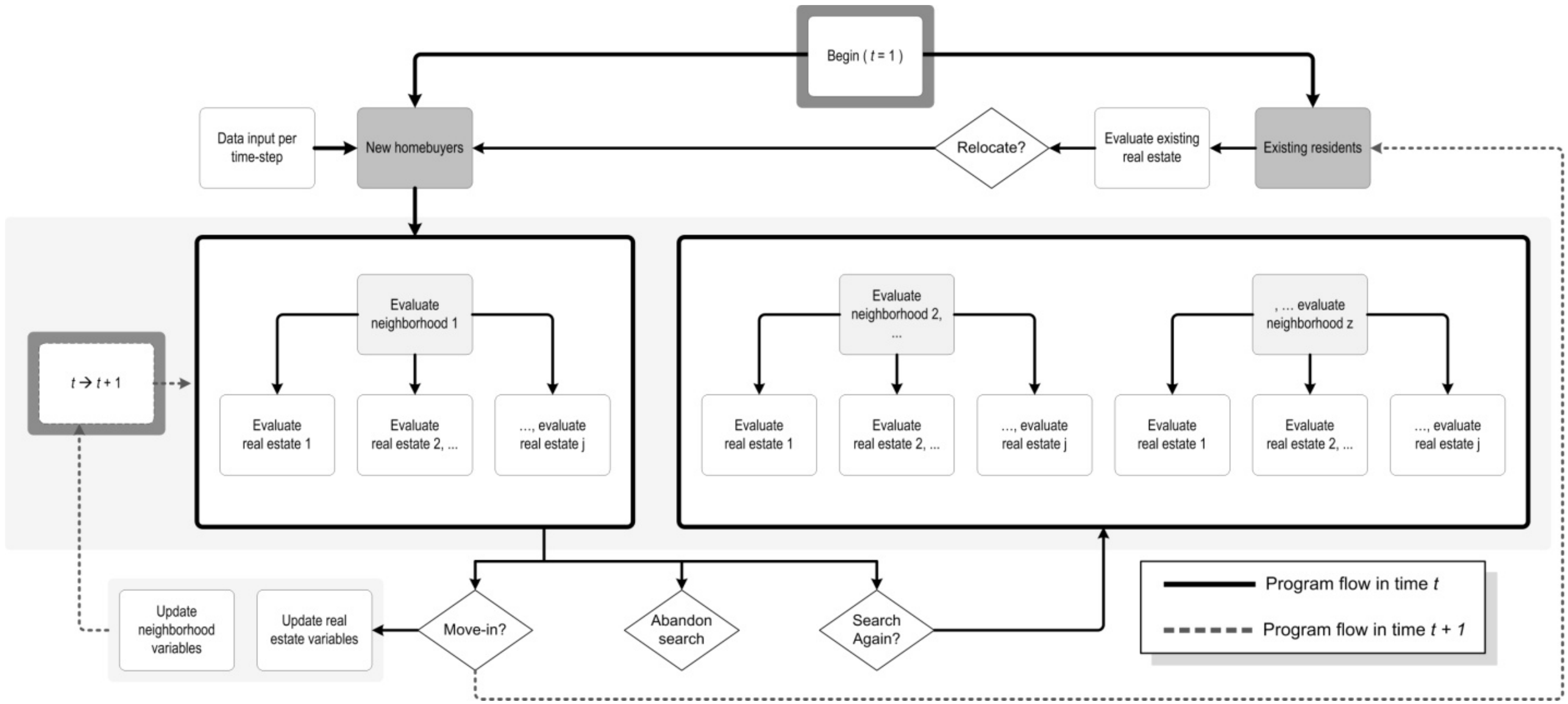

Figure 3. The programmatic flow of information in the micro-model.

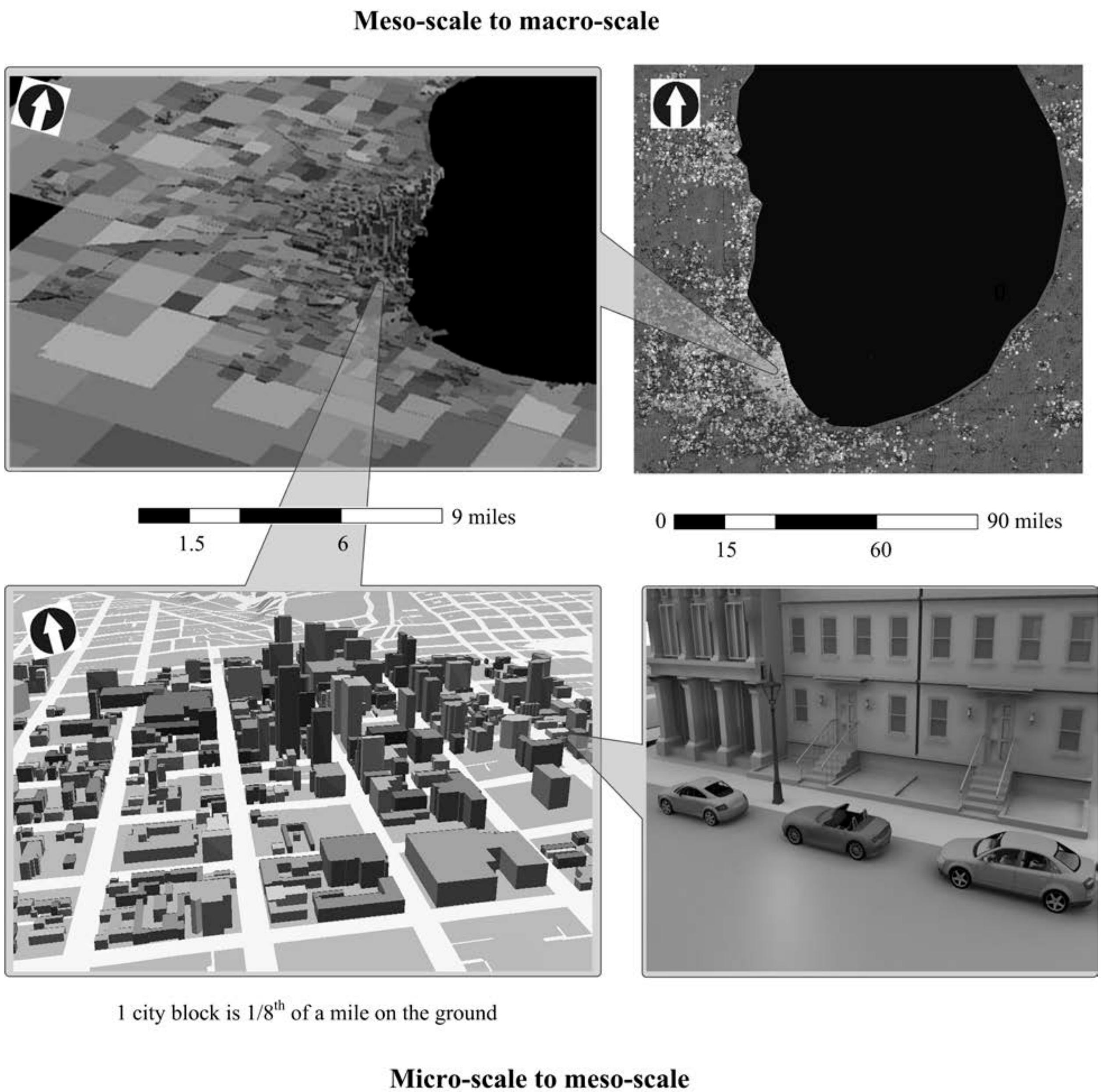

Figure 4. The meta-model treats a variety of urban scales and processes, from the city-system (macro-scale) to the intra-urban neighborhood (meso-scale) and the individual housing unit (micro-scale).

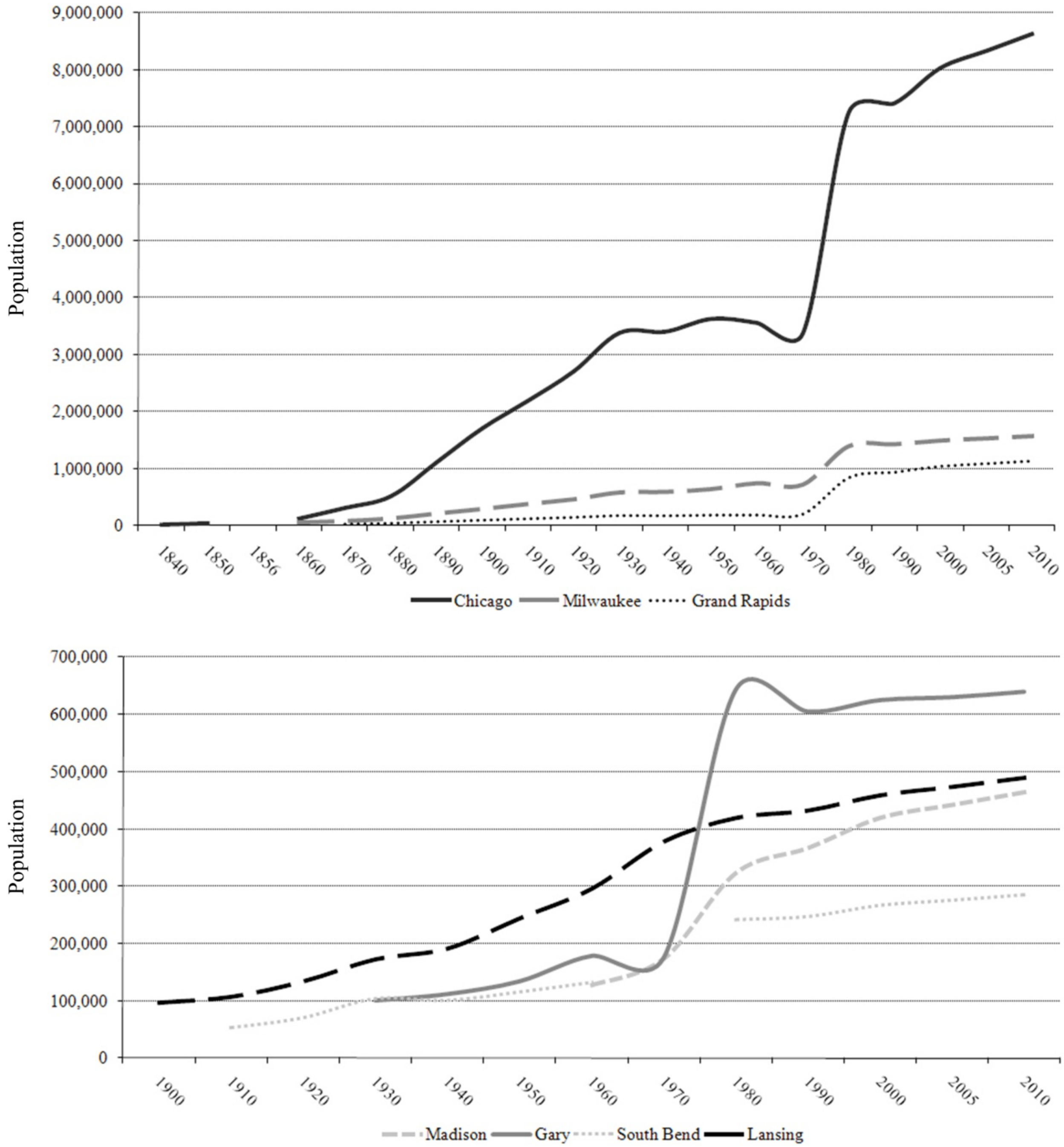

Figure 5. The volume of new population input to the model can be calibrated to historical population data and demographic estimates of future growth from the U.S. Census Bureau.

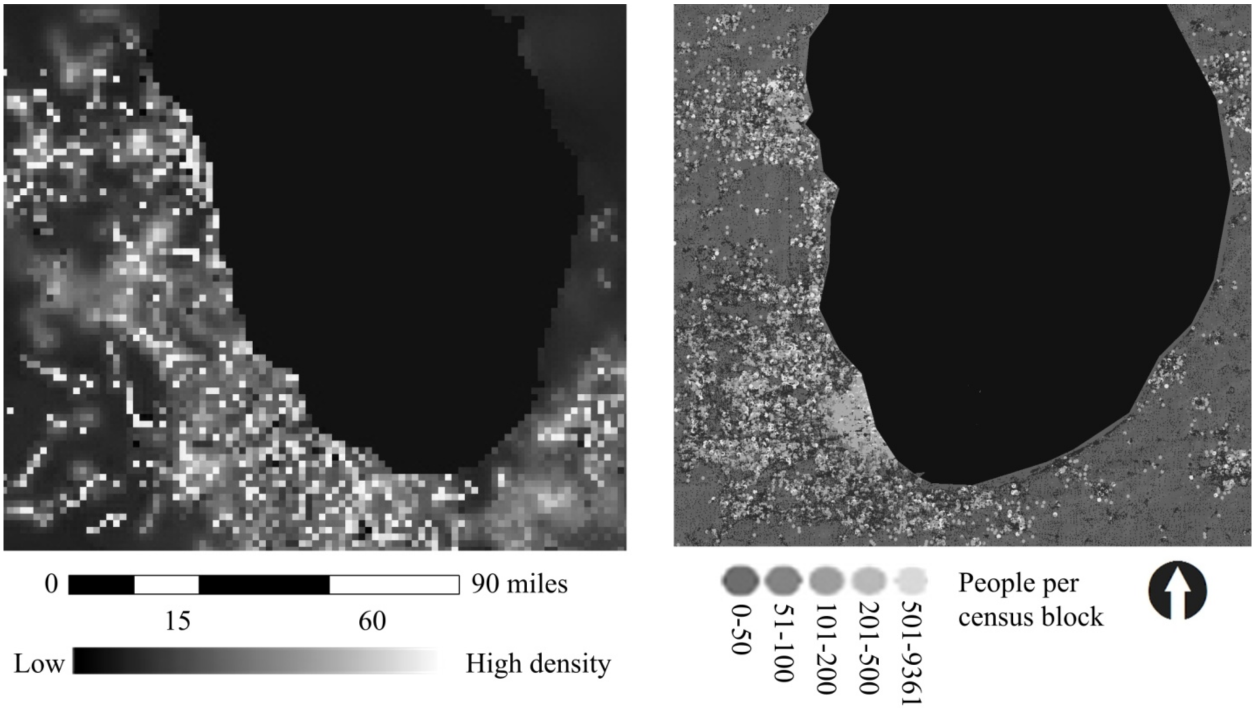

Figure 6. A comparison of the simulated (left-hand-side) and actual (right-hand-side, from U.S. Census Bureau data) end-state (year 2000) urban geography of population around the Chicago metropolitan area.

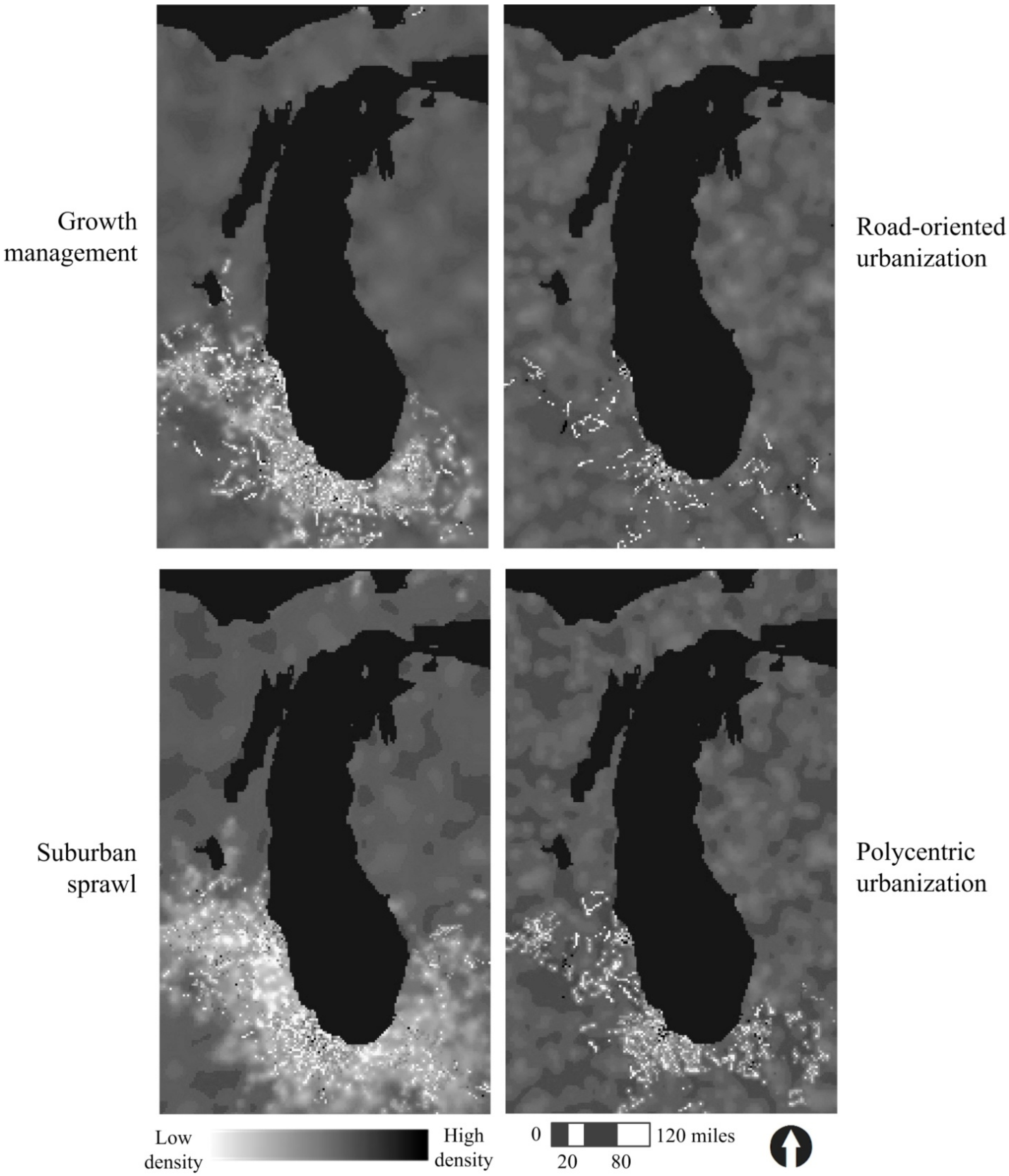

Figure 7. By controlling the different urban process heuristics in the model, either manually or automatically, different urban growth trajectories can be followed and allied to various urban planning policies, management scenarios, or hypotheses.

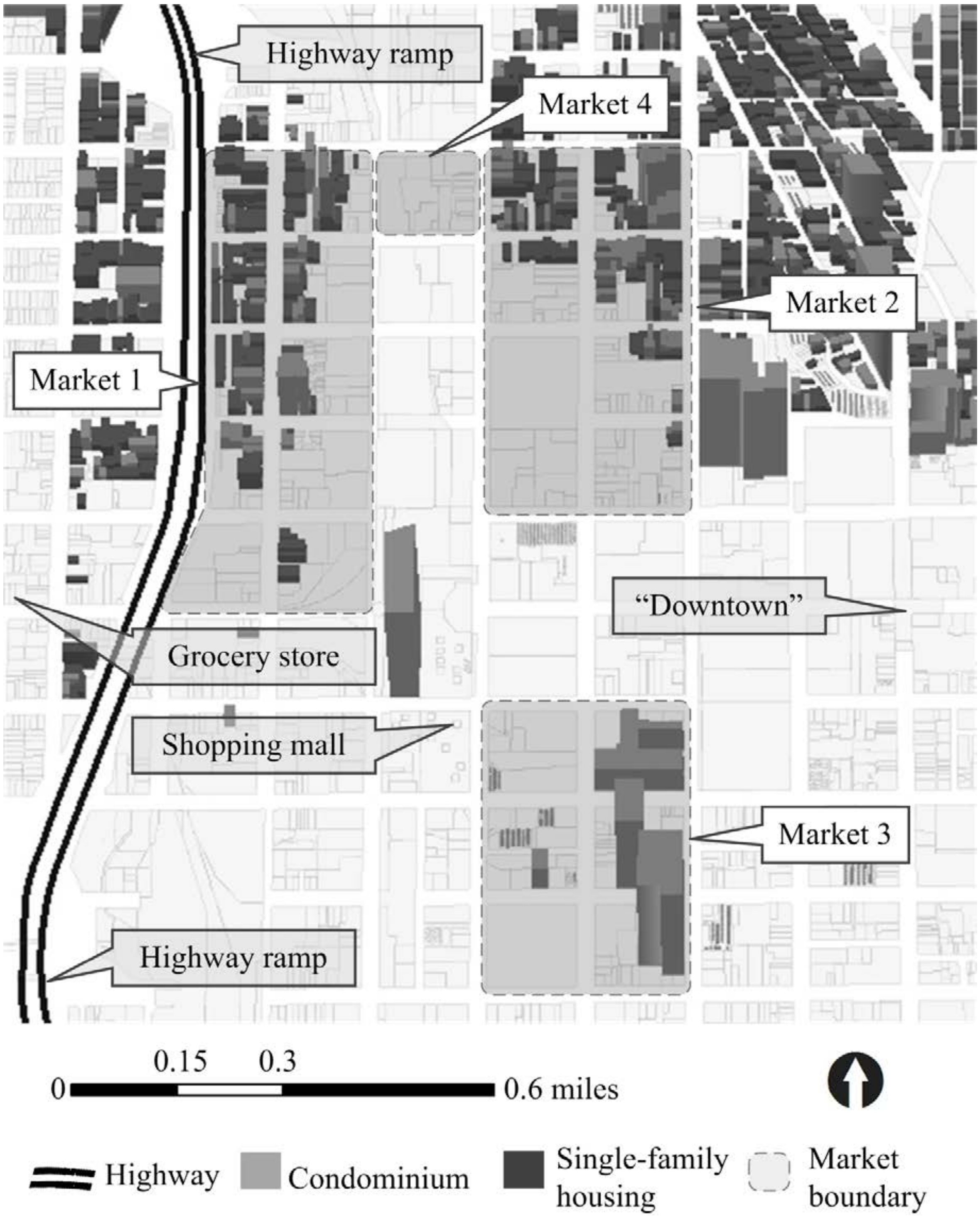

Figure 8. The delineation of markets within the micro-model, and their positioning relative to key features in the neighborhood.

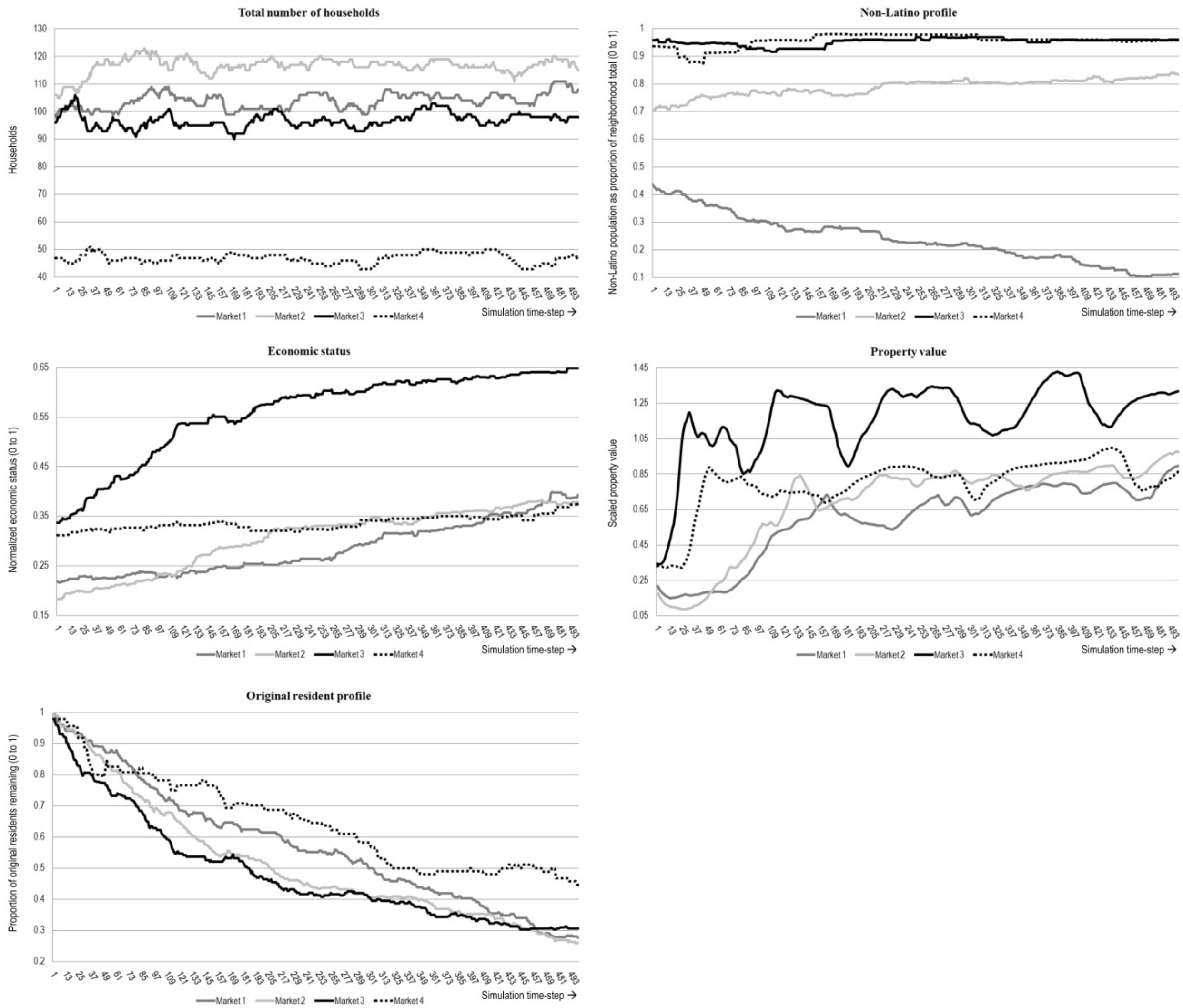

Figure 9. The dynamics of agent population, social, economic, and real estate characteristics in the demand and supply scenario of the micro-model