Chapter 13
Space in Agent-Based Models

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Abstract The chapter offers an overview of the issues related to the integration and representation of space in agent-based models (ABMs), with a focus on those models that can be considered spatially explicit. Key aspects of space in ABM are highlighted, related to: the role of space as an attribute of agents and the environment; as an interaction component; as a determinant of issues of scale; and as a tool for communicating and validating model outcomes. The chapter reviews the issues and challenges arising from the difficulties of integrating space in agent-based modeling. It outlines the emerging trend towards improving the level of realism in representing space, which can lead not only to an enhanced comprehension of model design and outcomes, but to an enhanced theoretical and empirical grounding of the entire field of agent-based modelling.

13.1 Introduction

One of the main characteristics of agent-based systems is that the interactions of the modeled agents do not take place in a vacuum, but are situated within structures that both condition agents' behavior and are in turn influenced by it (Epstein and Axtell 1996). These interaction structures can be physical or social environments, or networks that encode geographic or other feature-based differences (Riolo et al. 2001). Consequently, a key advantage of ABMs is their ability to integrate these two components – agents and their environment – through systematic specification of interdependencies and feedbacks (Parker et al. 2003).

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It should be noted, however, that traditionally the emphasis in agent-based modeling has been clearly placed on the development of agents and their behavior at the expense of less sophisticated representations of space and spatial relationships (Brown et al. 2005). Many ABMs, in fact, consider spatial relationships as a marginal issue, or at least treat space as a feature of the model that becomes relevant only at the macro scale. Examples of such models include investigations of social and cultural phenomena such as investment management, dynamics of labor markets, shifts in consumer behavior, or spread of technological innovations. In contrast, another string of ABMs, more tightly related to investigations of geographic phenomena, considers space as an integral component of their system. These models, referred in the literature as spatially explicit ABMs, include a diverse group of studies ranging from explorations of urban growth and natural resource management to agricultural economics and archaeology. Commonly, these models try to establish explicit links between environmental characteristics and agent behavior (Benenson and Torrens 2004).

The discussion offered in this chapter on issues related to space and its representation in ABMs is centered on those models that can be considered spatially explicit. The review of the literature on which this paper is based is far from balanced as it relies heavily on examples from the field of urban modeling. This is due partially to the author's background, but more importantly to the fact that in urban modeling the consideration of space is inevitably explicit (Berger et al. 2002). The proliferation of spatially explicit ABMs in the last 10 years is particularly impressive in the area of land use analysis where such models have become popular tools for understanding land-use systems (Polhill et al. 2001; Deadman et al. 2004). Here ABMs are considered particularly well suited for representing complex spatial interactions under heterogeneous conditions (Parker et al. 2003).

The discussion of space offered on the following pages is structured into two parts. The first one provides an overview of the general concepts of space and its integration within agent-based modeling. The key aspects of space in ABM are highlighted related to: the role of space as an attribute of agents and the environment; as an interaction component; as a determinant of issues of scale; and as a tool for communicating and validating model outcomes. A further discussion in this section addresses the various ways in which space is represented in the ABM world. The second part of the chapter reviews the issues and challenges arising from the difficulties of integrating space in agent-based modeling. The most promising venues towards a better representation of space are outlined, reviewing the shift from cell-based to object-based applications. The chapter concludes by sketching the contours of an emerging trend aimed to move the theory and practice of ABM beyond the grid-vs-vector debate, offering some new prospects for the integration of space within agent-based modeling frameworks.

13.2 The Concept of Space in ABM

13.2.1 The Integration of Space in Modeling Frameworks

This section outlines several aspects of space critical for its integration within spatially explicit agent-based modeling systems.

13.2.1.1 Space as an Attribute

An apparent role of space in ABMs that try to incorporate the significance of spatial phenomena in the simulation of social processes is the function of space as an attribute of a model's components – both of the environment and of the agents that operate within it.

The spatial characteristics of the environment could be represented with various levels of detail (this topic is discussed in more detail later in this section), but at a minimum, the model environment could be described as a non-differentiated plane with geographic or relative coordinates on which the actions of the agents take place. In such models the environment influences the agents' interactions simply by measures of distance and direction (Castle and Crooks 2006). In models that represent the physical characteristics of the environment with a greater level of sophistication, the agents respond to attributes of the landscape such as physical barriers, soil types, infrastructure, or aesthetic qualities by adopting their behavior to the features of the modeled environment.

Space as a characteristic of agents in ABMs is a more flexible concept. The agents could be spatially explicit or they could be implicit (meaning that their precise spatial location is not essential for the operation of the model). In addition, spatially explicit agents could be static (tied to a specific location in the environment) or dynamically situated (free to move within the environment either with or without predefined constraints).

13.2.1.2 Types of Space-Agent Interactions

Due to the wide variety of details with which both the environment and the agents within an ABM could be specified, the nature of the interactions between them could be rather complex. First, it is possible for an agent to be associated with only one spatial feature in a one-to-one relationship. A typical example of such a relationship is a household and its place of habitation in a simple residential location model or a local government and its jurisdiction in an urban growth management simulation. An agent, however, could be associated with more than one spatial feature in a one-to-many relationship. Examples of such cases are models in which households are linked with their places of residence, work, shopping, entertainment, etc.

In addition to the level of connectivity, there are two ways in which environment-agent interactions could be constructed: as a simple unidirectional relationship in which the environment is affected by the behavior of the agents (or vice versa), or as a multidirectional cycle of interactions and feedbacks between the two. Examples of models integrating space in a simple one-way causal environment-agent relationship are relatively few. In such models the environment is the only factor governing agent behavior. The agents adopt strategies that allow them to react to a heterogeneous environment given their goals and actions (Parker et al. 2003). Alternatively, the causal relationship could be pointed the other way by modeling changes in the environment as a result of the agents' behavior. Examples here include studies of deforestation due to agricultural practices, fragmentation of the natural habitat due to urban sprawl, etc.

In reality, the interactions between humans and their environment are always more complex, never confined to a single unidirectional link – a fact which is recognized by the majority of agent based modelers. A good example of the complexity of environment-agent interaction is urban gentrification, where a chain of events dynamically transforms both the actors and the environment. In this process, agents are drawn to urban areas due to specific locational or environmental characteristics; they engage in interactions with other actors in the local property market thus changing its dynamics; as a result the environment is changing; this in turn draws new actors to the scene affecting further the dynamics of the process. Another good example of modeling the complexity of environment-agent interactions is the SLUCE model of residential location at the urban fringe (Rand et al. 2002; Brown et al. 2005). Here residents make decisions about where to locate based on a combination of environmental factors including density, distance to service centers, and the aesthetic quality of the landscape. New service centers locate near recent residential development, influencing, in turn, the behavior of future homebuyers. A main challenge for the models exploring the complexity of environment-agent linkages is to separate the effects of endogenous interactions from spatially correlated exogenous landscape features (Irwin and Bockstael 2002).

13.2.1.3 Space and Scale

Scale is another important aspect of the task of integrating space in ABM frameworks. The issues of scale become relevant in the construction of the model in two distinct ways linked to the determination of the spatial extent and the spatial resolution of the data used (Goodchild 2001). First, in terms of the spatial extent of the modeled area, studies have demonstrated that changes in spatial extent have a significant impact on the outcomes of spatial analysis (Saura and Millan 2001). This fact highlights the need to capture processes at the scale at which they operate. This principle of scale-dependency is also particularly important in determining the level of spatial resolution, or the level of detail captured in the model (Lam and Quattrochi 1992). A coarse granularity of the data tends to iron out both spatial heterogeneity and spatial dynamics (Batty 2005). The issues of spatial aggregation are particularly relevant for ABMs that try to capture emergent behavior (Goodchild 2001). The “modifiable areal unit problem” (MAUP) and associated issues of ecological fallacy (Openshaw 1983) loom large in all models based on assumptions that larger units are representative of smaller units. While this does not seem to be an issue with the specification of agents, which is commonly done at the level of individuals and households, finding the proper level of representation of environmental characteristics and processes presents significant methodological difficulties. The use of a very fine data resolution, on the other hand, has been found to produce patterns that are overly fragmented (Menard and Marceau 2005; Chen and Mynett 2003). Finally, making the integration of space in ABM an even more challenging task, is the recognition of the fact that an individual agent is likely influenced by, and in turn influences, processes occurring at multiple spatial scales (Batty 2005; Parker et al. 2003).

The consideration of scale also becomes pertinent in ABM through the definition of neighborhoods of interaction. In the classic cellular automata (CA) conceptualizations on which the majority of ABM environments are based, neighborhoods are defined on the principle of spatial proximity. Here the magnitude of interaction is described as a distance decay function following Tobler’s law, which postulates that near things are more related than distant things (Tobler 1970). While the size of the neighborhoods in many CA and ABMs is predetermined by a fixed (and in many cases somewhat arbitrary) radius, a relatively small number of studies have carried out systematic analysis of the impact of this critical neighborhood parameter. A recent study of residential segregation, for instance, has emphasized the importance of scale over the shape of neighborhoods, which in this case is interpreted as the field of the agents’ vision (Fossett and Dietrich 2009). Other studies have proposed more refined techniques of neighborhood definition taking into account different spatial scales relevant for the modeled interactions (Batty et al. 1999; Vancheri et al. 2008). In recognition of the larger spatial scale at which neighborhood interactions operate, some scholars have introduced the concept of domains – large scale spatial ensembles representing a group of neighborhoods populated by agents of homogeneous characteristics – devising algorithms for the identification of emerging domains and techniques for following their evolution (Benenson et al. 2005).

It should be noted, however, that operational ABMs of larger scale systems such as metropolitan areas are still quite rare (e.g. Benenson et al. 2002; Mathevet et al. 2003), pointing to a lack of studies taking on the challenge of modeling processes that operate on multiple spatial scales (e.g., from the level of individual parcels and neighborhoods to the scale of urban regions). The task of simulating large-scale dynamics based on detailed representation of micro-scale processes poses many new challenges in terms of computational algorithms, data organization, and model architecture (Ettema et al. 2007).

13.2.1.4 Space as a Tool of Validation and Communication

Another important aspect of integrating space in ABM is its utility as a powerful tool of communication and validation of model outcomes. These two areas – communication and validation – have been identified as key challenges for the future development of the ABM field (Crooks et al. 2008) having received so far only scant coverage in the professional literature. This fact is somewhat surprising, considering that in many cases a comparison between model outcomes and real data along their spatial characteristics is the ultimate form of model validation. Yet one needs to be aware that location-specific estimates based solely on landscape metrics may not be as useful as having model outcomes reproduce realistic patterns, or as Mandelbrot simply put it – they must "look right" (Mandelbrot 1983). And while ABMs have the potential of being more easily comprehended by the general public due to the fact that they simulate "real world" behavior based on simple rules, quite often the outcomes of these models are not immediately transparent for a wide range of potential users who happen to lack the appropriate technical background for interpreting the results. In this sense, the visualization of model outcomes through maps and other types of commonly used spatially referenced information can serve as a great medium of communicating a model's results, reaching effectively a wider range of users (Axtell 2000).

13.2.2 The Representation of Space

The level of detail with which the environment is described in spatially explicit ABMs depends primarily on the type and the purpose of the model. Thus while in theoretical interaction models environmental characteristics are traditionally simplified (Irwin and Bockstael 2002), in models that are based on real-world locations the representation of landscape heterogeneity is a critical feature of a model's design. These two approaches have been referred to in the literature as *designed* (in the case of the more abstract theoretical models) and *analyzed* (in the case of applied inductive studies) (Parker et al. 2003). It should be noted that the distinction between the two approaches in not always clear-cut, with a substantial number of models straddling the boundary between abstract and more realistic representations. At the same time, since the early days of ABM, there has been a gradual yet noticeable trend towards more detailed representations of socio-spatial systems (Epstein and Axtell 1996). This could be explained by the natural course of the evolution of the field striving for higher fidelity of the modeled reality on one hand; and the increasing pressure to develop tools that are geared towards end-users and other stakeholders on the other (Matthews et al. 2007).

In general, the majority of spatially explicit ABMs rely on a regular cell framework used as a basis for representing the environment (Barros 2003; Batty et al. 2003). This concept of spatial organization is borrowed directly from the field of CA due to the kinship between the two modeling techniques in the analysis of related socio-spatial phenomena. With the conceptual linkages between ABM and CA being so tight, often CA models are re-interpreted as ABMs by attributing anthropomorphic state variables to cells (Torrens and Benenson 2005), using transition rules as proxies to decision making (Parker et al. 2003). However, regardless of these attempts, an important distinction remains. While CA can be described entirely through the interaction of spatial phenomena, they do not provide support for typical actor-based processes (Ligtenberg et al. 2001). As a result, CA models rely on a fixed interaction topology whereas the interactions in ABMs can be changed dynamically since they are defined at the level of mobile agents (Brown 2005).

The general model formulation, based on CA populated by agents migrating between cells, seems to be a natural process of merging ABM and CA by building on the strengths of each modeling approach (Portugali et al. 1994; Portugali and Benenson 1997). The ability of such systems to separate out the influence of actors, institutions, and the environment have been enthusiastically embraced more specifically in urban high-resolution modeling (Parker et al. 2003; Manson 2006). Here, the urban environment is represented in two layers, one for the city's infrastructure (immobile), and the other for migrating human individuals (mobile) (Portugali 2000; Polhill et al. 2001). Correspondingly, in many land-change models, agents choose cells from a gridded landscape for their productive utility, either for agriculture or home building (Evans and Manson 2007).

A key conceptual dilemma in the construction of model environments in ABMs is in the choice of selecting the best way to represent the environment's critical properties. Choosing between raster vs. vector-based representations is not always an easy decision to make. While raster-based structures are best fitted to capture continuous field data, vectors are best suited to depict the properties of discrete objects. Since the natural and built environments are composed of both, the question is which way would be most appropriate for capturing the essence of the modeled spatial phenomena. Traditionally, the prevailing practice in both CA and ABMs has been to favor a rigid partitioning of space into regular cells, and there are several factors that have solidified this choice. Some of the main reasons include the conceptual foundations of CA theory and its grounding in cell space; the prevailing availability of remote sensing data in raster formats; the advantages of using the functionality of raster-based GIS data preparation and analysis in model development; and the computational efficiency of working with regular grids (Stanilov 2009).

Deviations from the practice of using a rectangular tessellation of space in CA and ABMs have included experimentation with hexagonal grids (Phipps 1989; Sanders et al. 1997), yet it has been recognized that in order to make models applicable in the arena of public policy, modelers need to move away from abstract cellular representations in order to incorporate the detailed geography of the real places (Xie and Batty 2003). While the literature has long suggested the integration of irregular structures in microsimulation (Couclelis 1985), only recently have ABMs begun to use real-world spatial data (Brown et al. 2005). Early attempts have considered non-uniform partitions of urban space, accounting exclusively for infrastructure units (Erickson and Lloyd-Jones 1997; Semboloni 2000). One of the first ABMs to use real-world geographic features was developed in the field of natural resource management, in a simulation of the recreational use in a state park in Arizona (Gimblett et al. 2002). More recent work based on the integration of parcel-level data has included the development of custom-built model environments such as MABEL (Alexandridis and Pijanowski 2007), but most common has become the use of hybrid raster-vector environments in which vector-based features are used to calculate spatial attributes of raster-based cells such as calculating accessibility of cells based on the distance to the road network (Brown et al. 2008).

The evolution of the grid vs. vector dilemma within the field of agent-based modeling is discussed in more detail in the following section which offers a summary of the main challenges related to the integration of space within ABMs.

13.3 Issues and Challenges

One of the main challenges for agent-based modeling is to move both practice and theory from the arena of experimental and hypothetical applications towards empirically-based research (Berger and Schreinemachers 2006; Janssen and Ostrom 2007). This process entails a transition from abstract towards more realistic representations of the environment (Torrens and O'Sullivan 2001). While CA and agent-based systems have been introduced in the modeling world with the intent to infuse it with a recognition of the finer scale on which spatial relationships operate in both the natural and the built environments, these models, in their majority, continue to be based on highly restrictive assumptions related to the integration and representation of space. This situation has been primarily a function of the limitations imposed by the direct utilization of the generic spatial constructs underlying CA theory, rather than the application of empirical or theoretical knowledge on how systems function in space (Torrens and Benenson 2005).

13.3.1 From Cells to Objects

The deficiencies of employing a rigid tessellation of space as a basis of ABM environments stem from the fact that pixel-based cellular dynamics seldom match spatial phenomena (Xie and Batty 2003). To begin with, many linear features of both the natural and the built environment (rivers, infrastructure, etc.) do not lend themselves to be easily represented in a grid format that engenders the proper integration of network elements in the specification of spatial interactions (Benenson et al. 2005). Additional problems arise with the depiction of entities and agents that are either larger or smaller than a single grid cell. The representation of entities larger than the size of the basic modular unit calls for aggregation of cells based on a unique shared attribute describing the identity of the depicted object. The grouping of cells on this principle, however, creates conceptual and computational problems challenging the basic premises on which cell-based structures operate. In cases when cells are larger than the spatial entities on which they are superimposed, the issue of cell heterogeneity presents significant methodological challenges. The problems created by such a tessellation could be as difficult to address as the MAUP in aggregate models where the boundaries are at least drawn with the idea of maintaining a certain level of area homogeneity.

There have been several attempts to increase the fidelity of the model outcomes by fine-tuning the size of the grid cells of the lattice underlying CA and ABM environments. While common sense logic would suggest that smaller cell sizes increase data resolution, thus leading to more accurate results, in some cases the findings of sensitivity analysis indicate that a coarser resolution can generate more realistic spatial patterns (Jenerette and Wu 2001). Support for this claim has been provided by studies concluding that using the finest resolution does not provide the best results (Menard and Marceau 2005; Chen and Mynett 2003). Overall, there appears to be a general agreement shared in the field that the choice of cell size has considerable impact on simulation results (Kocabas and Dragicevic 2006), and that one needs to perform a systematic sensitivity analysis to determine the optimal cell size for a particular model (Jantz and Goetz 2005). This task, however, takes a significant amount of resources and ultimately the selection of cell sizes in many projects is determined somewhat arbitrary, mostly relying on previous studies.

The problems stemming from the application of abstract rectangular grids as a spatial framework for modeling are compounded further by the use of rigid raster cells for defining the spatial extent of neighborhoods of influence. While the utilization of a universal nondiscriminatory grid might be appropriate in modeling environmental processes where influence is mainly determined by proximity (e.g., the spread of brushfires) in urban environments spatial relationships tend to be much more complex in their dimensions and magnitude of interaction.

The field of CA/ABM abounds with experimentation aimed at optimizing the definition of neighborhoods (much more so than with studies questioning the applicability of raster lattices). In the majority of cases, this has included experiments with extending the radius of influence beyond the traditional von Neumann and Moore neighborhoods (White et al. 1997). Some have used hierarchical neighborhoods defined on a neighborhood, regional, or global level. Others have proposed to define neighborhood interactions based on empirical analysis derived from neighborhood characteristics by calculating over- or under-representation of particular parameters (e.g., land use class) relative to their representation in the entire study area (Verburg et al. 2004).

The issues associated with the application of rigid grid lattices has spurred a strand of research exploring the utility of alternative conceptualizations of spatial structures underlying model environments, including the Voronoi model of spatial tessellation (Shi and Pang 2000; Flache and Hegselmann 2001) and the use of graph-based CA (O'Sullivan 2001; Torrens and Benenson 2005). This path of exploration has drawn its own share of critics, pointing to the fact that Voronoi polygons do not correspond to real-world entities, but are generated automatically for simplicity of computation.

Recently, attempts to link closer the tessellation of space to real world entities have been emphasized in the field of urban modeling with several studies employing parcels as the basic unit of spatial organization (Stevens and Dragicevic 2007; Alexandridis and Pijanowski 2007). The use of parcel-based cells in urban ABMs offers several avenues for refining the definition of neighborhoods and transition rules that are not available in the conventional raster-based modeling environment. The utilization of a cadastral–based lattice provides an opportunity to incorporate important parameters of spatial interaction that cannot be accounted for in the traditional grid-based models. Such systems of structuring the modeled environment can be linked to the following methodological advantages (Stanilov 2009):

- An environment in which cells are based on parcel boundaries allows for the integration of cell size as a factor of spatial interaction, reflecting the fact that smaller parcels exert a smaller impact on neighboring cells and vice versa.
- Parcel-based cells can account for variations in the magnitude of cell interaction that are due not only to differences in the size of neighboring cells but in their mutual orientation as well. Such relationships are captured by the length of their shared boundaries.
- Parcel-based cells also have the advantage of being homogeneous in terms of their land use. This allows for a more precise definition of land use interactions, thus eliminating the problems associated with cell heterogeneity.
- Parcel-based cells can take cognizance of variations in the intensity of development better than nondescript raster cells. The use of parcel boundaries can capture, for instance, the fact that a large parcel with a small building footprint can have less of an impact on its neighboring cells than an intensely developed smaller parcel.

The use of cadastral property lines as a basis for creating the underlying lattice of a model environment is of fundamental importance for capturing the essence of urban form generation. Research in urban morphology has consistently stressed the essential role that land ownership patterns play in setting up the spatial configuration of urban environment. Parcel boundaries, although not physical entities per se, outline the basic spatial framework within which the urban landscape is constituted (Conzen 1960). The use of historic cadastral boundaries makes particular sense in the context of modeling the growth of the urban periphery where the pre-urban cadastre has set the basic framework within which the pieces of urban development are distributed.

The integration of parcel data in ABM indicates a new direction for the development of the field marked by the transition from raster to vector-based data and from cells to objects as descriptors of both agents and their environment. Indeed, some of the most exciting and promising theoretical advances in ABM in recent years have been related to experimentations with the object-oriented data modeling approach. Such developments have been driven by the similarity in abstraction shared between the agent-based and object-oriented paradigms (Castle and Crooks 2006). The fact that most ABMs use object-oriented programming languages, such as C++, Java, or Objective-C, points naturally to conceptualizations describing the environment as a collection of spatially discrete objects (Benenson and Torrens 2004). The possibilities for the effective implementation of the object-based approach seem to be most frequently recognized in the development of high-resolution simulations of urban dynamics.

One of the most conceptually advanced systems of this type is the Object-Based Environment for Urban Simulation (OBEUS) (Torrens and Benenson 2005; Benenson et al. 2005). Here discrete objects directly represent real-world urban entities and both agents and features are treated as individual automata situated in space through a set of geo-referencing rules. The model distinguishes between fixed objects (described with the coordinates of their vertices, edges, centroids, minimal bounding rectangles, etc.) and non-fixed urban objects identified by pointing to one or several fixed ones. Neighborhoods are defined by Voronoi coverages constructed on the base of centroids, and by interaction rules which allow neighborhoods to be varied in space or time in the course of the simulation. Such object-based models have the added advantage in their ability to assign temporal and location behavior as an attribute of features rather than space itself, allowing objects to be updated asynchronously (Castle and Crooks 2006).

In spite of the numerous advantages of employing an object-based modeling framework, there have been a relatively limited number of cases embracing this approach in the field of ABM. The reluctance to venture into this territory is related to several factors. First, compared to models based on raster data, vector-based structures require significant computational resources and object-based programming knowledge. In addition, the departure from traditional cellular-based space representations leads to several conceptual problems (Castle and Crooks 2006). A major obstacle is that, while the neighborhood relationship between identical cells in a CA-based model do not vary, in an object-based vector model the magnitude of the neighborhood interactions is impacted by the spatial attributes of the objects (Benenson et al. 2005), which makes them conceptually and procedurally difficult to model.

Another problem in object-based modeling arises from the challenge of dynamically updating connected or adjacent features whose shapes change over time (Miller 1999). In such cases the space-time topology of objects' vectors becomes increasingly complex as amendments accumulate during the simulation runs (Castle and Crooks 2006). Of particular interest in urban modeling, for instance, are the processes of parcel subdivision or amalgamation which underline the morphogenetic processes of growth. Yet, due to the issues outlined above, these processes have not found adequate representation in ABMs so far. The few attempts to incorporate dynamic repartitioning of space rely on rather mechanically construed Voronoi tessellation algorithms (Semboloni 2000; Benenson et al. 2005) that do not bear much resemblance to the complex patterns generated by the processes of land subdivision. In spite of the growing number of experiments with the object-based approach, moving forward from agents with fixed vector boundaries remains to this day a seemingly insurmountable challenge in ABM (Hamman et al. 2007).

13.3.2 Beyond the “Grid vs. Vector” Debate

Another interesting area of development within ABMs, situated outside the territory of the grid vs. vector and cells vs. objects debate, is composed of a recent group of studies concerned with the integration of urban form characteristics that have been previously overlooked. An early example of such an attempt is the ILUTE project (Miller et al. 2004) in which the built environment is described by the type and amount of floorspace, while transition rules incorporate the age of development as well as local and global vacancy rates. Similar attributes of the built environment are used in another detailed land use change model, which adds to the spatial parameters the amount of land surface covered by buildings, thus identifying spatial resources available in each cell for further development (Vancheri et al. 2008).

A further effort to capture key features of the built environment in an ABM structure is aimed at incorporating representation of physical design elements. The DEED model (Brown et al. 2008) locates residential agents using a utility calculation that considers the landscape characteristics associated with a range of subdivision types. Each of the four types is defined on the basis of observed land-cover proportions and patterns, street patterns, and lot sizes. The characteristics of subdivision design are also incorporated in a high-resolution data model which evaluates how different subdivision designs might influence development under varying population growth rates and buyer preferences (Stevens and Dragicevic 2007).

A logical step in the progression towards higher levels of sophistication with which the environment is represented in ABMs is the incorporation of the third dimension of space. The field of ABM has traditionally been dominated by two dimensional approaches, with very few experiments venturing into 3D space (Dibble and Feldman 2004; Thorp et al. 2006). Most of these projects are conceptual developments creating hypothetical environments such as CityDev, which offers an interactive multi-agent simulation model of city development organized spatially in cubic cells (Semboloni et al. 2004). A few studies, however, have tried to incorporate 3D features into models simulating the development of real urban environments. Of particular interest among these examples is the quality of views offered within a given landscape. In such studies, viewshed analysis is used to describe the degree of visibility as a determining factor for residential location (Yin and Muller 2007).

An interesting venue of exploration within the ABM world is the use of 3D environments for the purposes of visualization (see Patel and Hudson-Smith 2012 for an overview of visualizing ABM outputs). One of the first illustrations of such capabilities utilized a combination of Repast software libraries and GIS layers (Dibble and Feldman 2004), allowing the movement and interaction of agents to be followed in real-time 3D networks. The system has been used to model a number of socio-spatial phenomena including the transmission of infectious diseases, the dynamics of civil violence, and the coordination of social networks. Latest attempts to develop further conceptually the application of 3D visualization include the idea of moving ABM simulation environments from individual workstations to collaborative geographic space using Second Life as a platform for the dissemination of geographic content (Crooks and Hudson-Smith 2008). Such experiments underscore the great potential for the development of the field charted by the advancement of the concepts of space within ABMs.

13.4 Conclusions

The primary strength of ABMs is as a testing ground for a variety of theoretical assumptions and concepts about human behavior. As a result of this concentration on behavior-driven social processes, ABMs tend to be traditionally less concerned with realistic representation of the physical environment. Therefore, they are rarely used as predictive models for real-world sites where the concern is that they can be overly fitted to existing data, thus losing their power of generalization or ability to explore alternative systems.

As the field of ABMs develops and matures, it has faced the need to refine its underlying theoretical concepts, including the role played by the environment in conditioning the interactions of agents. Research has highlighted the point that dynamic behavior-based processes can be significantly impacted by even small changes in underlying spatial structures (O'Sullivan 2001). This has directed the attention of agent-based modelers towards new paths for better integration and representation of the spatial aspects of the modeled environment.

The most numerous group of such studies have been constrained within a general effort to refine CA-based structures, which continue to be utilized as an underlying environment for the majority of ABMs. These efforts have included the employment of higher resolution data, larger areal extents, and experiments with alternative methods of grid tessellation. An interesting departure from the dominant tradition is based on the work of a relatively small but growing number of researchers who have tried to break away from the bind of CA constructs by experimenting with environments defined by vectors and objects. This approach holds the promise of producing very interesting results, especially in view of the natural affinity between the agent-based and object-oriented paradigms. The third stream of innovations in the integration of space in ABMs is built on the idea of achieving a richer representation of the spatial characteristics of the environment through the inclusion of features that have been previously overlooked but which might have a critical importance for the dynamics of the modeled phenomena. An important conceptual leap forward here is the inclusion of the third dimension of space which opens up exciting opportunities for exploration of model parameters and the visualization of simulated phenomena.

All of these new avenues of exploration present new challenges for the development of the field of agent-based modelling. Many of the conceptual and technical considerations related to the integration of space are pushing the field forward as modellers are charged to apply forward thinking, which should not be confined by the limitations of the tools and concepts in currency today. This chapter has presented the argument that improving the level of realism in representing space can lead not only to an enhanced comprehension of model design and outcomes, but to an enhanced theoretical and empirical grounding of the entire field of agent-based modelling. It appears that this new decade will be a critical time for meeting these goals.

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