Chapter 1
Perspectives on Agent-Based Models and Geographical Systems

Michael Batty, Andrew T. Crooks, Linda M. See, and Alison J. Heppenstall

Abstract This chapter guides the reader to the material in this book. It begins by outlining the meaning and rationale for agent-based models/modelling (ABM), focusing on their history, how they evolved and how they sit within the broader context of modelling and simulation for geographical systems. Three themes which we see essential to ABM are then outlined, namely the question of detail versus model and data parsimony of which ABM represents the former, questions of model validation that flow from this, and lastly issues about the extent to which ABM is a generic or specific style in terms of applications. We examine the essence of such models in terms of the way behaviour is modelled using various rules, and then we discuss technical issues such as computation, visualization, error, and schemes for model design. All this sets the context for the various chapters that follow. We conclude by explaining briefly what is contained in each chapter and by guiding the reader in how best to use this book.

M. Batty (✉)
Centre for Advanced Spatial Analysis (CASA) University College London, London, UK
e-mail: m.batty@ucl.ac.uk

A.T. Crooks
Krasnow Institute for Advanced Study, George Mason University, Fairfax, VA, USA
e-mail: acrooks2@gmu.edu

L.M. See
International Institute of Applied Systems Analysis (IIASA), Laxenburg, Austria
e-mail: see@iiasa.ac.at

A.J. Heppenstall
School of Geography, University of Leeds, Leeds, UK
e-mail: A.J.Heppenstall@leeds.ac.uk

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1.1 A Little Bit of History

It has been over 50 years since the first attempts were made to explain geographical systems using formal tools from mathematics. In the 1950s spurred on by rapid developments in digital computation that were immediately grasped as a new media in which to conduct virtual 'experiments' on human and physical systems, geographical theory underwent a radical shift in emphasis. Systems were articulated using ideas from physics and biology which found expression in a wide array of mathematical formalisms widely exploiting the role of analogy and metaphors involving representations and processes in the physical and natural sciences. Yet from the beginning, there was an assumption, usually implicit, that for geographical theory to be meaningful, it must deal with aggregates, ironing out the noise and much of the variation that was associated with spatial systems. Particularly in human geography, there was a tacit assumption that populations needed to be represented as aggregates whose attributes were averaged over different variational characteristics in such a way that homogeneity might be ascribed to their behaviour in space and time. This was not pursued in the mistaken belief that populations were actually homogeneous but in the interests of simplicity and parsimony, the search for such regularity appeared to be the correct way forward.

The experience 50 years on has been salutary. It has been exceptionally hard to find theories and models that are robust enough to withstand the sort of testing and validation that is associated with the harder sciences, particularly with classical physics. In the effort to simplify and distil the essence of geographical systems and their processes into the same kinds of simple but powerful laws that characterize the physical world, formal theory has tended to reduce geography to the point where much of the richness and variety that we associate with the world is defined away, often leaving simplistic notions that are both obvious and banal. Those developing such models are well aware of these limits through the tortuous process that has beset the field during these years. Yet in all of this, slowly but surely the idea that we need to represent geographical systems at a much more elemental level has taken hold. There has always been resistance to the idea that we should search for some atomic element or unit of representation that characterizes the geography of a place, and the social sciences in particular have been reluctant to consider the notion that models of their systems should be postulated and tested at the individual level. But as progress with aggregate models of homogenous populations has faltered, there has been a perceptible shift from aggregate to disaggregate, from populations to individuals, from macro to micro. In this, the notion of an 'agent' has become the focus of this new quest.

If you define a social system as a collection of agents, then immediately you tend to consider agents as individuals in a wider population, individuals that act purposively, that learn and innovate, thus introducing ideas that are hard to consider using more aggregate styles of representation. Agents generate actions that occur in time as well as space, that influence their wider environments and that cooperate as well as conflict with one another over the use of space. Defining many agents in a population immediately gives some sense of their diversity, and in this way, any heterogeneity in the system is directly picked up. It is easy to see why the idea of agent-based modelling (ABM)[1] has become so popular in the last two decades for it begets a style of modelling that has the capability of reflecting the richness of the world in a way that appears essential to any good explanation of how spatial structures such as cities, regions, the global system itself as well as all its physical components evolve and change. The power of the agent paradigm is consistent too with the fact that as our world has become more complex, largely due to increasing wealth and innovation in technology; data about ourselves is becoming more available, particularly through online sources. Ways of handling such data using ever powerful methods of computation are going hand in hand with these developments, all leading to the notion that simulating worlds composed of agents rather than their aggregates might now represent a feasible and productive way forward.

We consider that a book which synthesizes our collective wisdom on agent-based models in geographical systems is both opportune and timely; opportune because there is much to say about how we are beginning to build agent-based models and how geography imposes its own requirements on such developments, timely because so far there are few, if any, reviews of the state-of-the-art in this area, and those wishing to enter and contribute to the field require as much source material as we can muster. Here we have collected together a series of contributions that cover a very wide range of issues and approaches to agent-based modelling, beginning with a review of modelling styles and types that inform the field, moving then to more conceptual approaches, and then to methods and techniques that are involved in designing and constructing such models. These form the first three parts of the book and thence prepare the reader for a multitude of applications which we organize in terms of the scale of the agent – micro or macro. These form the last two parts which to an extent also correspond to spatial scale. They constitute about half the contributions contained herein, thus balancing theory, method and technique evenly with applications.

1.2 Essential Themes

There are many themes that we will identify in this opening chapter to which we will alert readers. In no sense do we consider these to be exhaustive but there are three we consider essential to an appreciation of all that follows: these involve the dramatic differences between the style of modelling which has dominated geographical theory and applications in the past from those which we consider now form the cutting edge. It is quite clear that ABMs represent geographical systems at a level of richness and variety that is an order of magnitude greater than their aggregate precursors. ABMs usually have many more components – where we think of these

[1]ABM is also taken to mean Agent-Based Model (s) as well as Modelling.

as agents themselves – than their aggregates, and this means that their attributes are specified at a level of detail that is associated with each individual agent. Interactions between agents are usually involved and thus the level of representation grows exponentially as the number of agents increases. Even if the number of agents is quite limited, often in cases where ABMs are used for pedagogic experiments, then the level of detail for each agent and their interaction is still substantial in comparison with their aggregates. In short, ABMs break the basic rule of science that theory must be parsimonious – as simple as possible – and that a theory or model is better than any other if it performs equally well but is simpler; this is Occam's razor. In fact, the argument for ABMs is quite the opposite. For many systems, we have plausible but non-testable hypotheses about how we think the system works, and if we exclude these simply because we cannot test them against data, then we are guilty of distorting our theory simply due to the expediency of not being able to test it using classical means: against independent data. This issue is of enormous significance for it throws into doubt the whole process of developing and testing models of geographical systems, indeed of testing and validating or falsifying any theory.

The conventional process of theory development in science begins with observation, proceeds to an induction of some theory from that data, and then proposes some hypothesis that is testable against some other independent set of observations, usually in a different time and a different place. This is the classic process of experimentation where the experiment is repeated and validated (or not), the theory then being refined (or rejected) in entirely different situations by independent scientists. In this book, most authors who are applying ABM to real situations do assume that their models must be validated against real data. Most however are also uncomfortable with this process for usually their models are only testable to a degree and much of what is specified in the model associated with the behaviours of agents is simply non testable in that data on processes, decisions and actions is not available and/or observable. Outcomes of agent behaviours may be testable but the processes involving such behaviour are not.

Accordingly ABM has seen the process of model testing being elaborated in much more detail than traditionally associated with aggregate modelling. In particular, tests for plausibility, experiments with running models under many different sets of initial conditions, sensitivity testing of model parameters as well as traditional algorithms used to maximize the goodness of fit have come to dominate the process. Added to this, the idea that models which are richer by an order of magnitude than their counterparts should be verified as well as validated against data has become significant. This means that models should be run to test whether they are behaving as their originators intended and this has little or nothing to do with how well they might reproduce observable data. Surrounding this discussion is the notion too that models are no longer built for prediction per se but as much to inform general scientific inquiry as well as any debate between stakeholders over what the future might hold (Epstein 2008). In short, these kinds of model are as much to structure debate and dialogue as to provide measures of how the future might turn out. This is a controversial issue that is increasingly important to social science as well as science itself as the classical canons of scientific inquiry melt away into the vestiges of history.

There is a third theme that relates to ABM and marks a major difference from the past. Just as the term model has come to embrace theory, the term computation has come to embrace model. Since digital computers became the environment in which this type of modelling is possible, methods of computation have come to influence the construction of models as much as theory has done. In this sense, modelling has become more generic rather than specific with generalized approaches to modelling for many different types of system being developed during the last 30 years. Initially models of geographical systems were tied very closely to theory and each individual model contained a sufficient amount of its originator's personal knowledge of the problem to be quite distinct in terms of its computation. Of course as soon as computer programs of any scope and size became available for specific classes of model, there was a demand to generalize the program to any application. In fact, the very act of model development presupposes that simulations would emerge which would be generalizable to different situations. Indeed a true test of any model has always been predicated on the basis of taking the model elsewhere and evaluating its performance on independent data (Lowry 1965). In this sense, computation itself needs to be generic.

The experience however has been somewhat different from this notion that good models are entirely generalizable for it would appear that only the simplest of models meet this criterion, and when they do, they tend to be of pedagogic value only. Most spatial models tend to be developed for very specific situations whose data and context is sufficiently different from any other for the model to be only usable in any immediate sense for the problem at hand. Moreover in the past, models have tended to be closer to theory than to generic computation but as more experience has been gained with modelling, generic approaches have been fashioned. In geographical modelling, the spatial dimension has been so strong as to inhibit the development of generic modelling until quite recently but there are now sufficiently different frameworks of a generic nature available for model-builders to consider adopting a framework first and then adapting this to the particular theory and problem that define the simulation that is required, rather than the other way around.

Agent-based modelling is one of the most important generic modelling frameworks to have been developed to date. It has emerged largely due to the convergence of object-oriented programming ideas in computer science with the need to represent the heterogeneity involved in many kinds of physical and human system at much greater levels of detail, issues that we have already noted in some detail above. Although geographical models were best represented by specific land use transportation interaction (LUTI) models tailored very specifically to urban theories based on urban economics and social physics, as soon as formal modelling began, generic approaches appeared, as for example in systems dynamics which was based on general ideas about formulating models as partial difference equations subject to capacity constraints. These, as Batty (2012) shows in the next chapter, did not find much favour in geographical analysis largely because they were hard to adapt to spatial systems but other approaches based on econometrics for example, have formed the basis of some spatial models, although this style of modelling is specific to economic analysis, notwithstanding its generalization to mainstream statistical modelling. As we recount in the chapters that follow, cellular automata (CA) modelling developed before ABM but the software used to implement these styles of models is quite elementary. Although some generic modelling packages such as SLEUTH and METRONAMICA have been developed (see Iltanen 2012), generic CA packages for geographical systems are not widely available. Microsimulation models are even more specific, notwithstanding their almost tool-like focus, and generic software has not appeared, again perhaps due to their focus in our field on space which is hard to embrace.

It may even be worth making a distinction between generic or specific models with respect to the way they are formulated and the software and tools which tend to be used in different model types. The problem is that in some senses tools such as those that exist in econometrics and statistics can be elevated to entire model systems while model approaches like microsimulation often feature as tools in generating data. In short, microsimulation can be used in spatial interaction models as can agent-based approaches. In such cases, the model in its traditional format is augmented by the addition of agents or a decomposition using synthetic data analysis techniques which are core to microsimulation. For example, in some of the social physics models that are examined towards the end of the book such as those involving rank size (Gulden and Hammond 2012), spatial interaction (Dearden and Wilson 2012) and population change (Pumain 2012), agent-based approaches are used in their implementation but their structure is one dictated by the original model framework not by ABM itself. Even more confusing is the fact that model systems merge into one another and this is very clear in the case of CA and ABM, but as we will see, microsimulation models can transition into ABM as shown in Wu and Birkin (2012). In fact Torrens (2012) augments CA and ABM with GIS and calls these geographical automata systems (GAS).

Only ABM has developed very general packages which can be applied to a wide array of systems and problems. For example, the packages that are popular range from sophisticated programming systems such as SWARM, plug-in Java-based environments like Repast and MASON, and simpler scripting languages like NetLogo (and its originator StarLogo). A good review of these tools is given by Crooks and Castle (2012) where they show that to an extent these packages encapsulate CA models. In several of the contributions that follow, CA represent the environment in which agents behave in spatial terms. The other feature that is important when generic modelling packages are used is that their generalizability is always limited in some way. This can also force the modelling effort to embrace tools and techniques that are not suited to the system in hand and if certain functions are absent, it can lead to models that lack certain key components that more specialized software will enable. In fact, it is now so easy to customize many of these packages and to add other software as plug-ins using standard methods of linkage that most generic software is capable of being easily extended to deal with system specifics. However the downside of all this effort is that models which are the most effective tend to be those that involve considerable programming effort. We have not yet reached and may never do so the point where model users can specify a model for a problem type and simply assume that it is computable from generic software.

1.3 Structural Rules, Behaviour, and Dynamics in ABM

Agents almost by definition are purposive. They are endowed with behaviours that are usually proscribed in a series of rules that are activated under different conditions. This is in the manner of stimulus and response (or push and pull, or some such reactive logic), and in this sense, agents always engender change. Dynamics which may not be explicit but is almost invariably implicitly temporal, thus comes onto the agenda and in this sense, ABM deals with dynamic modelling. This is in stark contrast to LUTI models for example which are comparatively static for the most part or microsimulation models which as Birkin and Wu (2012) note, can be either static or dynamic. A particularly simple kind of ABM is in fact a CA where the transition from one state of a cell to another state– in each geographic area – is based on a set of rules that might be seen as representing how the state of the cell behaves as all the cells around it change. This somewhat anthropomorphic interpretation of CA might be appropriate if the cell contains an individual who is fixed in location but whose attributes define their state which is continually changing. A good example of this is the simplest model of segregation due to Schelling (1978) where the cell state is an individual with one view or another, who may then change their view dependent on the number of surrounding cells with individuals holding similar or different views. Here the cell is the agent; the agent does not move in space but does move in terms of their opinion. Indeed CA models are excellent examples of structures where many rules of a relatively simple nature in and of themselves combine to generate extremely complex behaviours when operated on a large lattice of cells (Batty 2005).

Agent behaviours may be reactive (sometimes called passive) or proactive (anticipatory). Invariably such behaviours are engendered by the agents in question scanning their environment in which other agents exist. More complicated forms of ABM involve different classes of agent, with agents being a mixture of types along the spectrum from reactive to proactive. Agents may be any distinct object in the system that is involved in changes of state, ranging from actual individuals in human systems to elements of the built environment. Moreover unlike agent types can interact with one another. In fact, in object-orientated programming, any element in the computation can be an object which is endowed with properties. In particular in visual programming, all the various elements of the graphical user interface are agents or objects. This ability to define different types of objects gives ABM its power but it also defines its limits in that it is hard to see a completely general system where any kind of agent might be defined in terms of generic properties and attributes of any other.

Yet despite these constraints, it is possible to see very wide ranges of problem being simulated using ABM. The more specific involve literal interpretations of agents as individuals in the human population such as those used in pedestrian and crowd modelling, the best examples here being those discussed by Patel and Hudson-Smith (2012) and Johansson and Kretz (2012). At the other extreme, ABM can be used to simulate interactions between groups of humans or even groups of policies that do not have a direct association with specific individuals as, for example, in a whole range of land cover models such as those used in developing countries where land and aid are key to development. In all these cases, at the heart of ABM lie processes of change which in our context have an impact on the geography of the system in question. These rules embody the key elements of the processes involved reflecting the way agents operate which lie at the core of the model. Agents interact with one another and with their environment, changing each other and their environment and in this sense, ABM is able to deal with open systems in a way that more specific modelling approaches cannot. These processes cannot be prescribed outside the modelling context except to say that they reflect a wide range of techniques. Simple rules of logic as in CA models are rather standard but many criteria are also built on algebraic functions that in geographical systems often relate time and space, action at a distance and across time. In fact the many contributions in this book show this variety in the way model processes are articulated, ranging from the standard algebraic formulations of micro economic theory (see Magliocca 2012) all the way to the rule-based logics used by Liu and Feng (2012) in their extension of CA modelling for urban development.

There are three elements related to dynamics and behaviour that are worth flagging as these appear many times in the various contributions that follow. First there is the question of cognition that relates to how agents perceive change in their wider environment and how they learn. Learning is often simulated through simple exposure to events over time and by watching what the majority do. In ABM, navigation and way finding in geographical space tend to be the most obvious elements in which the cognitive apparatus of the agent is utilized. There is little formal theory about how agents might best learn as the rule-based structure of many ABMs mean that such behaviours are defined in ad hoc empirical ways that are often tested using trial and error experiments. Second there is the question of scale. Behaviours occur across many scales but in their most elemental, these lie at the finest scales where the individual is located. Various ABMs and certainly CA models assume some principles of self similarity which operate across spatial scales and lead to the emergence of patterns at higher levels consistent with fractal structure. This is central to complexity theory. As ABMs are applied to coarser spatial scales, models change in focus and often even in type as the agent paradigm weakens although it is more likely that the way the model operates and the processes that are defined change rather than the framework itself. ABMs become less predictive and more speculative as scale changes from finer to coarser, from small scale to large.

The last point worth noting is that ABMs deal almost by definition with interactions, with their environment but also with inter-agent links. This introduces directly the concept of networks which appear implicitly in many of the contributions presented in this book. In fact, we do not emphasize networks very strongly in this book and there are no specific contributions apart from those dealing with movement of pedestrians and more aggregate populations. In a sense, this mirrors the fact that only quite recently have researchers in the geographical sciences begun to grapple with networks (although these have been implicit in spatial interaction and LUTI models for many years). One of the main developments in network science is their linkage with epidemiological models where propagations of rumour, innovation, disease, indeed any process that spreads through space and time can be cast in an ABM framework, as illustrated in Simoes (2012). We will pick such issues up in our conclusions when we anticipate the future of this field where we see agents moving across networks as being central to new applications.

1.4 Computation, Calibration, Error and Uncertainty

Before we launch into a brief guide to the contributions that follow, we will address a series of more technical questions that pervade any and every approach to modelling. In principle, ABMs can generate enormous data requirements in that the assumption is that every agent in a population that in the past was treated in aggregate (or not at all), must be represented explicitly in some computable form. This can give rise to massively parallel computation where agents are farmed out for individual processing on multiple processors but it also leads to simplifications which involve aggregation into super-individuals in the manner suggested by Parry and Bithell (2012). Moreover computation is massively increased because each agent has to be tracked and in situations where there are thousands of such agents, it is usually necessary to visualize their behaviours so some sense of the order and pattern generated in their simulation can be evaluated. We have not yet mentioned visualization but in these new generations of model, both CA and ABM, visualization has become essential based on links to GIS, CAD and other multimedia systems as noted by Patel and Hudson-Smith (2012).

Data requirements notwithstanding, most ABM so far, with the exception of large transport models such as TRANSIMS (Casti 1997) and MATSIMS (Rieser et al. 2007), do not appear to use intensive computational facilities or generate massive demands for parallel or related high performance computing. This is partly because many of the processes that characterise ABM cannot be matched with real world data and thus are never testable, despite the fact that most ABM have multiple parameter sets that make a complete enumeration of their possible solutions impossible. There are proposals to build extensive global models of entire populations such as that suggested by Epstein (PACER 2011) where some 6.5 billion individuals are being simulated with respect to their abilities and exposures to generate global pandemics. Visualization is essential for such models and this can set up severe computational demands. However most ABMs run in desktop environments and tend to be more pedagogic in focus due to the fact that once the number of assumptions which are non-testable yet plausible begins to dominate model structure, the models themselves become more like devices on which to develop thought experiments, to inform debate rather than to predict actual futures.

We have already noted the problem of calibration which has been extended dramatically during the last two decades to embrace not only validation and fine tuning through calibration but extensive sensitivity testing, checks for plausibility, verifiability of the model's implementation, and various aggregation checks against different layers of data. Error and uncertainty are key to models that have many processes and multiple assumptions for a good model might minimize error and reduce uncertainty as much as it might optimize its goodness of fit against actual data. In this sense, ABMs cover a wider range of issues in terms of their validation than other more parsimonious models for there are many issues that need to be judged qualitatively and have no equivalent in quantitative evaluation. Evans (2012) outlines the key issues involved in exploring ABM in terms of error and uncertainty defining a cornucopia of possible sources of error, noting contrasts between accuracy and precision and defining issues involving risk and uncertainty as these come to characterize actual models and their outputs. In one sense, all the models introduced here address these issues but few do so explicitly, as much because the line needs to be drawn between what is possible, what is worthwhile and what is feasible in terms of the level of resources related to the modelling effort.

One last issue involves the actual process of model design. Many chapters that follow deal with different approaches to model construction but it is Grimm and Railsback (2012) who address the issue directly in outlining a procedural approach to evaluating models and this is immediately applicable to the design of a good ABM. They review ABM using a structure which provides Overview (O), Design (D), and Details (D) which they term ODD. From this structure, they are able to derive design patterns that enable model-builders to produce a scheme for Pattern Oriented Modeling (POM). This guides the designer in developing good ABMs based on a considered view of how entities, states, and processes need to be incorporated into the best model possible. This scheme is gaining ground in this field and others writing in this book are beginning to use it.

1.5 The Structure and Rationale for What Follows

We have divided the book into two main sections which in turn are divided in parts. In the first half of the book which is organized in three parts, we review ABM in Part 1 with respect to other related but different approaches, then in Part 2 in terms of their conceptual structure, and lastly in Part 3 in terms of the tools and techniques used to operationalize such models. In the second half of the book, we deal with model applications and divide these into two. Part 4 deals with micro models which are the true preserve of ABM while Part 5 deals with macro models, largely how macro patterns of spatial development and interaction often structured around other model frameworks, are implemented using ABM. As we noted above, the division into micro and macro applications tends to be one of sectoral or topical aggregation rather than spatial scale although there is some correlation between them.

In Part 1, Batty (2012) begins with an overview of models in general attempting to compare ABM and CA with other approaches such as LUTI, microsimulation, and systems dynamics models. This is followed by Birkin and Wu's (2012) more detailed review of microsimulation models which are close in spirit if not in structure to ABM, while Iltanen (2012) attempts the same review for CA models. In this sense, we establish that the wider class of ABM dealt with in this book includes microsimulation and CA which in one sense are extreme variants of this general domain. This part is concluded with a survey of ABM itself by Crooks and Heppenstall (2012) who examine the history, scope and focus of the field so far, noting the correspondence between all three model types: CA, microsimulation, and ABM.

Part 2 deals with more conceptual issues. O'Sullivan et al. (2012) provide a somewhat oblique perspective on ABM, explaining a little about how ABMs actually work but also cautioning the reader to identify conditions under which this style of modelling is most appropriate. Manson et al. (2012) take this further when they relate ABM to the wider domain of the complexity sciences, arguing that this is one of the main tools to simulate systems which operate from the bottom up and generate emergent patterns at coarser spatial and more aggregate scales. Abdou et al. (2012) then provide a blow by blow account of how to design and build an ABM. They set this context by exploring two well known models – Sugarscape which is the spatial ABM developed by Epstein and Axtell (1996) and Schelling's (1978) model of residential segregation both of which illustrate how emergence occurs in such systems. But they reserve their key example to the construction of car-following models that generate traffic jams of the classic kind that are pictured using what traffic engineers have for many years referred to as the 'fundamental diagram' – the relationships between speed and flow, which in turn shows how as flow increases so does speed only to level off after a flow threshold has been reached and then decline when the traffic jams: another example of an emergent phenomenon. Kennedy (2012) provides a useful exploration of cognition in ABM introducing some key issues involving the simulation of behaviour and this is followed by Ngo and See's (2012) discussion of methods of calibrating and validating an ABM which are far more detailed and inquisitive than methods used for traditionally more macro, aggregative and parsimonious models. This part is concluded by Alam et al. (2012) who broach the question of networks in ABM, reviewing issues of interaction, which involve specifying neighbourhood sizes, segregation rules and the way ideas and diseases propagate.

In Part 3, Crooks and Castle (2012) begin with a detailed review of ABM in terms of its software and the generic packages that have been developed to implement a range of model types. They conclude that space is not that well represented by such models, although GIS can now be linked to most of these packages. Stanilov (2012) then presents a more reflective essay on how space is incorporated in CA and ABM and this is followed by Parry and Bithell's (2012) chapter on computational issues that they discuss through the medium of model scaling which is akin to aggregation which preserves the role of the agent. Evans (2012) then deals with error and uncertainty and Wu and Birkin (2012) show how microsimulation can be augmented by ABM, showing exactly how these two frameworks are consistent and of course complementary to one another. The last two chapters which conclude this part and the first half of the book are those by Grimm and Railsback (2012) who introduce their ODD framework noted above and by Patel and Hudson-Smith (2012) who deal with models of crowding which use both macro and microscopic simulation but which illustrate quite clearly the need for good visualization in this field.

The second half of the book deals with applications which demonstrate the concepts, principles, and techniques that are dealt with in Parts 1–3. Part 4 deals with micro ABMs which cover crime, pedestrian movement, educational demand and supply, health, housing choice and land. These are all sectors that can be described in fine spatial detail and where populations are disaggregated to the level where individuals are explicitly represented in terms of their spatial behaviours. Malleson (2012) begins with his model of burglary that involves modelling how burglars select residential homes to rob and learn from the experience. Mobile crime is a key feature of these models. Torrens (2012) then shows how GIS can be added to ABM in his models of pedestrian movement while Johansson and Kretz (2012) provide a detailed review of the various models involved. Rand (2012) explores how micro and macro ABMs fuse into one another while Harland and Heppenstall (2012) and Smith (2012) outline how the education and health sectors can be simulated using the notion of agents being matched and allocated to school and health facilities. Jordan et al. (2012) examine diversity in housing markets using ABMs while Parker et al. (2012) explore how land markets can be modelled in the context of residential land use changes, specifically urban sprawl. Magliocca (2012) concludes this section with a foray into how a housing market model can be developed using ABM, an example of where urban economic theory provides the overarching structure which can be implemented by defining individuals engaged in demand and supply as agents.

In Part 5, the focus shifts to macro models, which are both spatially and sectorally orientated to aggregates but with these aggregates being applicable to space and sectors not the individual agents that populate them. Barros (2012) develops various ABMs of the peripherization growth process in Latin American cities using CA representations where the focus is on developing analogues of real growth patterns which manifest the sort of inequalities that characterize such cities. Simoes (2012) develops a robust model of the spread of mumps in Portugal that is implemented using standard epidemiological models in a spatial and network context. Ngo et al. (2012) show how land use and farming interests and policies in a Vietnamese village can be simulated using ABM and then Banos and Genre-Grandpierre (2012) explore a CA-ABM like model of idealized network systems with traffic flow which, like Abdou, Hamill and Gilbert's paper earlier in the book, mirrors how jams build up in spatial networks. Liu and Feng (2012) then develop an extended CA model of urban growth which is illustrative of how error and uncertainty can be incorporated into such models while Cabrera et al. (2012) examine how ABM lies at the basis of land cover models of agriculture in a developing countries context. The book is concluded with three papers that deal with traditional social physics models which can be implemented using ABM. First Gulden and Hammond (2012) show how a variant of a network model of cities linking to one another can be used to generate city size distributions that mirror familiar power laws. Dearden and Wilson (2012) implement their Boltzmann-Lotka-Volterra models that link spatial interaction to constrained logistic growth by running the model through agents rather than aggregates. Finally Pumain (2012) explores her SimPop model framework, which she and her colleagues have been developing for over a decade, showing how agent interactions and actions generate the distributions and sizes of cities that have existed in Europe from the thirtieth century.

1.6 A Guide for the Reader

Many readers will be familiar with agent-based modelling to some degree and will wish to dip into the contributions that follow in an order that they will be able to determine from the titles and abstracts of the various chapters. But for those who are new to this field, we have organized the contributions beginning with more general overviews of the field, and then filling in more technical detail as we proceed. The first three parts provide a reasonable primer on ABM for those who have not explored the field before and the last two parts provide examples of applications to geographical systems. For those who wish to learn quickly about the field, then the contributions in Part 1 provide overviews, in Chap. 2 of six related modelling styles and types of which ABM is one, in Chap. 3 of microsimulation and in Chap. 4 of CA that are those styles of model that are closest to ABM, and lastly in Chap. 5 of ABM itself. If readers then wish to concentrate on filling in more detail about ABM, we advise them to look at Chaps. 6, 7, 8, 12 and 17 which focus exclusively on ABM and how such models can be defined, constructed and implemented. The rest of the contributions in the first three parts expand this overview to include related models and more technical details while Parts 4 and 5 deal with applications which are self explanatory. In no sense, do we as editors consider this set of contributions to be any kind of finished product. ABM is a work in progress and this represents as good a snapshot that we can currently assemble (in 2012) of this world as it is developing.

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