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Ballas, Dimitris; Broomhead, Tom; Jones, Phil Mike

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Dimitris Ballas, Tom Broomhead, and Phil Mike Jones

Abstract This chapter critically reviews the state-of-the-art in spatial microsimulation and agent-based modelling approaches with an emphasis on efforts to combine them in order to address applied geography problems. Spatial microsimulation typically involves the merging of census and social survey data to simulate a population of individuals within households (for different geographical units) whose characteristics are as close to the real population as it is possible to estimate (and for small areas for which this information is not available from published sources). Microsimulation is closely linked conceptually to another type of individual-level modelling: agent-based models (ABM). ABM are normally associated with the behaviour of multiple agents in a social or economic system. This chapter offers an overview of the state-of-the-art of both modelling approaches as well as a discussion of attempts to combine them, with an articulation of a relevant research agenda.

1 Introduction

> The era of a computational urban or regional geography based on the behaviour of individual households or firms not only provides a stimulating and exciting prospect for the years ahead but it is one which is now realistic and achievable.
>
> (Clarke 1996: 202)

D. Ballas (✉)
Department of Economic Geography, Faculty of Spatial Sciences, University of Groningen, Groningen, The Netherlands
e-mail: d.ballas@rug.nl

T. Broomhead
Department of Automatic Control and System Engineering, University of Sheffield, Sheffield, England

P. M. Jones
School of Law, Bartolomé House, University of Sheffield, Sheffield, England

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Over the past 20 years, micro-level simulation methods, such as spatial microsimulation and agent-based modelling, have been increasingly established as tools for applied regional, urban and local analysis, and they are also a research area where the work of Pavlos Kanaroglou with colleagues has made an impact (see, for example, Maoh and Kanaroglou, 2005, 2006, 2012; Ferguson et al. 2012; Ryan et al. 2009; Svinterikou and Kanaroglou 2006). This chapter critically reviews the state-of-the-art in spatial microsimulation and agent-based modelling approaches with an emphasis on efforts to combine them in order to address applied geography problems.

Spatial microsimulation typically involves the merging of census and social survey data to simulate a population of individuals within households (for different geographical units) whose characteristics are as close to the real population as it is possible to estimate, and for small areas for which this information is not available from published sources (Ballas et al. 2007a, b).

Microsimulation is closely linked conceptually to another type of individual-level modelling: agent-based models (ABM). ABM can be associated with the behaviour of multiple agents in a socio-economic system. These agents are capable of interacting constantly with each other and with the environment they live or move within. Their actions are driven by certain rules. Although this methodology sounds similar to microsimulation (where agents could be the individuals within households), it has long been argued (see, for example, Davidsson 2000) that ABM may offer a better framework for including behavioural rules into the actions of agents (including an element of random behaviour) and for allowing interactions between agents.

There are a number of good illustrations in a geographical setting (Batty and Densham 1996; Heppenstall et al. 2005, 2006, 2007; Malleson et al. 2010; Wu et al. 2008), and there is a research agenda to link these two complementary approaches more effectively. Microsimulation could be used to give the agents in ABM their initial characteristics and locations while ABM could then provide the capacity to model individual adaptive behaviours and emergence of new behaviours (also see Boman and Holm 2004). This chapter considers these possibilities, offers an overview of the state-of-the-art and articulates a research agenda.

2 Spatial Microsimulation

> Simulation is a critical concept in the future development of modelling because it provides a way of handling complexity that cannot be handled analytically. Microsimulation is a valuable example of a technique that may have increasing prominence in future research.
>
> (Wilson 2000:98)

Spatial microsimulation has been becoming increasingly established as a key quantitative method in human geography, building on a long successful history of non-geographical models (mainly developed by economists; for example, see Hancock and Sutherland 1992; Harding 1996; Mitton et al. 2000). Microsimulation has been used in the social sciences since at least the 1950s (Orcutt 1957, Orcutt et al., 1961) and, therefore, it has a long history of development and application: '. . . it can be argued that microsimulation modelling methodologies have long become accepted tools in the evaluation of economic and social policy' (Ballas et al. 2012: 3). Geographers and regional scientists have long been involved in adding a geographical dimension to this work and, thus, developing *spatial* microsimulation methods. These are underpinned by techniques used to estimate data about individuals when this data is not readily available. Individual units can be people, organisations, businesses or any other discrete entity. Most of the applications in geography to date have been focusing on people and typically involved the creation or synthesis of small area population microdata. This can be achieved by combining different small area census cross-tabulations or by merging survey data such as census and other geographical area data to simulate a population of individuals within households (for different geographical units), whose characteristics are as close to the real population as it is possible to estimate. In other words, the models simulate *virtual populations* in given geographical areas, so that the characteristics of these populations are as close as possible to their 'real-world' counterparts. The simulation outputs include a wide range of policy relevant variables such as pre-tax and disposable income, tenure status, household type, socio-economic group, consumption patterns, car ownership and so forth. The outputs can then be used to address questions such as the following (Ballas et al. 2007a, b):

- How does the lifestyle and quality of life of individuals and households vary across different regions, cities or neighbourhoods?
- What are the interdependencies of household characteristics with geographical factors such as the presence of hospitals, community centres or schools in an area?
- To perform *what-if* scenario analysis: i.e. answer questions such as 'what would happen to personal accessibilities if the patterns of service provision change?'
- What would be the geographical impact of national social policies on personal incomes and how effective would they be compared with alternative area-based policies?

As discussed above, the first examples of using spatial microsimulation techniques can be traced back to the 1960s, but they gradually became more common during the 1970s and 1980s as computers became more powerful and accessible. It can be argued that the conceptual framework was first set by Wilson and Pownall (1976) who presented a theoretical foundation of microsimulation models and suggested a new spatial modelling framework for representing the urban system based on the micro-level interdependence of household and individual characteristics. This seminal work was the basis for further groundbreaking work in the 1980s which involved the development of the first applied spatial microsimulation models (Clarke et al. 1984; Clarke and Wilson 1985; Birkin and Clarke 1988) based on an approach often described as synthetic reconstruction (see below). These in turn have been the basis for further development of increasingly sophisticated models making use of high quality data, software and hardware and involving for the first time the use of hill-climbing, simulated annealing and genetic algorithms (Williamson et al. 1998), iterative proportional fitting deterministic reweighting (Ballas et al. 2005a, b) and further applications and refinements of these approaches (Farrell et al. 2013; Tanton and Edwards 2013; Lovelace and Ballas 2013).

As also noted above, the key procedure behind the various spatial microsimulation methods is the combining of census data and survey data, by reweighting individual-level microdata (usually the product of comprehensive social surveys at the national level) so that they match census population totals. The 'small area level' at which the analysis is conducted varies depending on data availability and common variables in both datasets. There are numerous types of spatial microsimulation models. One distinction is between static and dynamic models, with the former based on 'a single snapshot', or cross-sectional view of a population at one point in time (Ballas et al. 2005a: 8). Alternatively, dynamic models are used to 'age the attributes of each micro unit', producing datasets that project the characteristics of these micro-units into the future. There are a number of different types of static microsimulation models, including:

- Synthetic probabilistic reconstruction models—these involve random sampling to select records from microdata sources
- Probabilistic reweighting models—these typically involve the reweighting of existing national microdata to fit geographical areas, using random sampling and optimisation techniques
- Deterministic reweighting models—these typically reweight microdata to fit small area characteristics, but without the use of random sampling, so results are consistent.

The first efforts to build synthetic reconstruction models include the work of Birkin and Clarke (1988 and 1989) and Williamson (1992). These methods were (and still are) particularly suitable and appropriate when there are no good quality population microdata. The method typically involves the use of iterative proportional fitting (also known as raking) methods combined with Monte Carlo sampling to synthesize small area microdata by combining different small area cross-tabulations (typically census tables). In particular iterative proportional fitting can be used to estimate joint probability distributions of particular characteristics (e.g. being in a particular age-group, socio-economic group and tenure status) on the basis of small area cross-tabulations. Monte Carlo can then be used to sample from probability distributions, which are then applied to individual characteristics (Birkin and Clarke 1989).

A key advantage of spatial microsimulation models is that they address the lack of spatially disaggregated data in surveys, due to the creation of the new datasets at either the individual or household level for small areas. Secondly, surveys may underestimate the presence of certain groups within a population therefore reweighting survey data at a national level would not include such groups in the data, whereas the matching techniques used in spatial microsimulation makes it possible to include such groups (Morrissey et al. 2008).

There are also a number of dynamic microsimulation approaches:

- Implicitly dynamic models—which use small area projections and then apply static microsimulation methodologies to create microdata statistically (e.g. see Ballas et al. 2005a)
- Probabilistic dynamic models—which use probabilities to project individuals into the future (e.g. see Ballas et al. 2005b)

A key advantage of the 'bottom-up' approach of spatial microsimulation is that outputs of such models can be used to study several social issues, such as social inequalities, at a variety of spatial scales. In the health domain, for example, Mitchell et al. (2002) have demonstrated the difficulty in using census data to study multiple factors associated with patterns of mortality, while also exhibiting the potential of microsimulation, specifically IPF, to solve such problems.

There have been a number of platforms and computer programming languages employed to build spatial microsimulation models ranging from FORTRAN programs in the early days to Java, C++ and more recently the use of R (Campbell 2011) with open source code available (Lovelace and Ballas 2013; Lovelace and Dumont 2016; Jones et al. 2017).

Over the past 20 years, there has been a rapidly growing number of applied spatial microsimulation models and studies in a wide range of themes building on the very successful and inspiring earlier work that was briefly discussed above. The application areas include the analysis of local labour market policies (Ballas and Clarke 2000), small area income and poverty (Ballas 2004; Panori et al. 2017), social and economic policy analysis (Ballas and Clarke 2000; Ballas et al. 2007a, b; Campbell and Ballas 2013), retail analysis (Nakaya et al. 2007), health inequalities (Jones 2017; Campbell 2011; Campbell and Ballas 2016; Edwards and Clarke 2009), education inequalities (Kavroudakis et al. 2013), industrial location and firm failure (Maoh and Kanaroglou 2012), residential mobility (Ryan et al. 2009), demography and population dynamics (Ballas et al. 2005a, b, 2006; Voas and Williamson 2000), water demand estimation (Williamson 2001), health inequalities (Tomintz et al. 2008; Procter et al. 2008; Edwards and Clarke 2009; Edwards et al. 2010; Campbell 2011; Campbell and Ballas 2016), (Kavroudakis and Ballas 2011) and transport analysis (Ferguson et al. 2012; Lovelace et al. 2014; Miller this volume).

This section provided a brief historical overview of microsimulation and spatial microsimulation (for more detailed overviews, see Ballas and Clarke 2009; Birkin and Clarke 2011; Ballas et al. 2013). It has long been argued (Williamson 1999; Ballas and Clarke 2009) that microsimulation is closely linked to another type of individual-level modelling: agent-based models (ABM). ABM can be associated with the behaviour of multiple agents in a socio-economic system, interacting constantly with each other and with the environment they live or move within. The following section provides an overview of ABM methods and discusses their key features and advantages.

3 Agent-Based Modelling

Agent-based models have been defined as 'computer representations of systems consisting of a collection of discrete microentities interacting and changing over discrete time steps that give rise to macrosystems' (Auchincloss and Diez Roux 2008: 3). Macal and North (2010) argue that the macrosystems emerging from these models, represented as patterns, structures and behaviours, are 'not programmed into the models, but arise through the agent interactions' (p. 151). Further, they state that the focus on modelling heterogeneous agents across populations, and 'the emergence of self-organisation' are key and distinguishing features that lead to agent-based models comparing favourably to other simulation methods, including system dynamics and discrete event simulation.

Agent-based models can be traced to the cellular automata models of the 1970s, including Gardner's (1970) Game of Life and Schelling's (1971) famous attempt to model human and societal behaviour, one of the first studies of its kind. Agent-based models gradually increased in complexity over time. Sugarscape, a model created by Epstein and Axtell (1996), is a good example of this in the social sciences, with agents free to move cell to cell and cells containing spatially distributed resources that agents could acquire from their environment. Agent-based models have evolved in line with computational capacity and are now used across a wide range of academic subjects including molecular modelling, biology, ecology, epidemic and pandemic modelling, computational sciences, economics, market analysis and numerous other 'real-world' systems including traffic, air traffic control, military exercises and physical infrastructure including electric power and energy markets (Macal and North 2010).

Similar to spatial microsimulation, agent-based models take a 'bottom-up' approach when investigating behaviours and characteristics at the individual level. The sum of these characteristics and behaviours and their interactions over time represent the system-level model (Teweldemedhin et al. 2004). This is opposed to top-down approaches which analyse global characteristics and system-level interactions. Systems are divided into smaller parts, but generally ignore individual-level characteristics, exploring these at a system level instead (Teweldemedhin et al. 2004). Bottom-up approaches are therefore more suited to analyses of individual interactions in small geographical areas. Features of such analyses are often simplified due to the difficulty in modelling human processes exactly. While there is a danger of oversimplification, this adheres to the 'KISS' principle ('keep it simple, stupid!') introduced by Robert Axelrod (1997), which emphasises the importance of simplicity in design so as not to make the model or its output too confusing to interpret.

While there is no agreed upon definition of what an agent is, Crooks and Heppenstall (2012) define three principles which each agent must adhere to:

1. Autonomy—agents should be 'governed without the influence of centralised control' (p. 87), able to absorb and exchange information with other agents they interact with. This, in turn, informs agent decision-making.

2. Heterogeneity—'Agents permit the development of autonomous individuals' (p. 87). Agents have unique individual attributes and any groups of agents that exist are created from amalgamations of these autonomous individuals.
3. Activity—'Agents are active because they exert independent influence in a simulation' (p. 87). Agents should therefore be: pro-active and goal directed, reactive and perceptive, interactive and communicative, mobile, adaptive and capable of learning and, finally, have 'bounded rationality'—it is assumed that the choices of agents are rational and that by bounding this rationality agents can 'make inductive, discrete, and adaptive choices that move them towards achieving goals' (p. 87).

Further, agent-based models contain rules that directly impact on agent behaviour and interactions. These rules are typically based on theory, expert knowledge or data analysis and can be applied across groups or individually. Rules are usually based around 'what-if' scenarios, while the behaviour of agents can also be specified when interacting with other agents and their environment. These interactions are key to the running of the models. Macal and North (2010) point out that 'the two primary issues of modelling agent interactions are specifying who is, or could be, connected to who, and the mechanisms of the dynamics of the interactions' (p. 154). Further, Torrens and McDaniel (2013) argue that 'agents' dynamics in simulation are not scripted; rather, they are processed or computed from a model that determines their behaviour given agent characteristics (states) and algorithms (rules) that feed on agents 'endogenous attributes' (p. 23).

Environments in agent-based models can be equally important. These are demarcated areas in which agents operate, or a 'miniature laboratory where the attributes and behaviours of agents, and the environment in which they are housed, can be altered and the repercussions observed' (Crooks and Heppenstall 2012: 90). The locations of agents in these environments may or may not be relevant, depending on the type of study being conducted. Agent-based models are extremely useful for observing events that only become obvious when the process has already started and is progressing (such as segregation), meaning that taking records of the event in real time becomes impossible (Batty et al. 2004). The method allows for the reconstruction of such processes and environments which can be followed from start to finish.

Examples of applied agent-based modelling work include the research of Malleson et al. (2013), who incorporated GIS into their agent-based model of crime hotspots in East and South East-Leeds (UK), and demonstrated that while crime generally decreased in regenerated areas, a small number of houses suffered increased burglary rates as a result of the regeneration. Batty et al. (2003) have also incorporated GIS into an ABM and showed how such approaches can evaluate specific events in urban environments. This research demonstrated how different routing methods for the Notting Hill Carnival led to reduced crowd densities and higher perceived public safety. Crooks (2008) has also emphasised the importance of both geography and geometry in such models by re-creating Schelling's (1971) segregation model with the inclusion of such features. This demonstrated that geometry can act as a barrier to segregation. Burke et al. (2006) have stated that the inclusion of physical space, individual heterogeneity and local interactions allows ABMs to produce different spatiotemporal dynamics when considering outcomes such as epidemic dynamics. The authors used the method to demonstrate that vaccinations, isolation of infected individuals and contact tracing can all help limit the spread of smallpox. There are also many examples of agent-based models of travel activity with an excellent overview of the state-of-the-art and research agenda provided by Miller (2018, this volume).

In addition, non-geographically explicit models also have great value as Auchincloss et al. (2011) demonstrate. Their model, based on behavioural economics, found that price was the key driver for food preferences even when low income families desired healthier food.

Some agent-based models have been concerned with the prediction and evaluation of certain future events and scenarios, particularly those related to the spread of diseases (Potter et al. 2012; Merler et al. 2013), and, in some historical evaluations, they have had access to past data to help parameterise models (O'Neil and Sattenspiel 2010).

A number of tools and software platforms enable the building of agent-based models. An increasingly popular platform is the multi-agent programming environment NetLogo (Wilensky 1999). NetLogo is object oriented, meaning that a system can be modelled as a set of objects which can be controlled and manipulated in a certain way depending on the purpose of the model or the system. This software has been described as being 'low threshold, no ceiling' (Tisue and Wilensky 2004), a central principle carried forward from modelling conducted in the original Logo language (The Logo Foundation 2016). As well as being relatively accessible to those without a history of writing scripts in programming languages, NetLogo also has the advantage of being able to read in a number of external file types. One such example includes the GIS extension, a function for reading in geographical data in both vector and raster format, which allows for models to be designed with specific landscapes, features, and contexts in mind. An example of the use of both types of GIS data in a NetLogo simulation is given in the work of Dawson et al. (2011) who designed a model investigating coastal flood management in the Welsh seaside resort of Towyn.

A key advantage of agent-based models is the ability to track agent characteristics of interest as simulations progress and interactions occur (Gorman et al. 2006). Through this it may be possible to gain better knowledge of the processes occurring at the small area level. Agent-based models can help research move beyond descriptive analysis as well as to test theoretical hypotheses which may offer better insights into a problem at hand (Johnson and Groff 2014; Cerda et al. 2014).

Nevertheless, what agent-based models lack when compared to microsimulation models is the richness in real-world information about the units of analysis (agents). In particular, agent-based models are often based on virtual units that 'behave' and 'interact' on the basis of a specified set of assumptions and theories but without the benefit of the use of 'real' data, such as the social surveys and census data typically used in the spatial microsimulation models reviewed in the previous section. It is, therefore, interesting to explore the possibilities of combining spatial microsimulation with agent-based modelling approaches. This would typically involve the replacement of microsimulated units driven by transition probabilities, with adaptive rule-based agents. The next section discusses this possibility with a brief review of the relatively limited number of studies to date that have attempted to carry out analyses based on such a combination.

4 Spatial Microsimulation and Agent-based Models

Amongst the few studies that attempted to combine spatial microsimulation and agent-based models is the work of Merler et al. (2013) who developed a stochastic microsimulation model combined with an agent-based model in their study of a flu outbreak in the Netherlands. The work of Wu et al. (2008) represents another rare example demonstrating the combination of these bottom-up approaches when investigating student migration patterns in Leeds. This hybrid model was shown to be very accurate in predicting the geographical spread of students within the city, compared to a microsimulation model which failed to capture the spatial clustering patterns of students. It is noted that microsimulation is driven more by statistics and probabilities, whereas agent-based models can rely on their rule-based (built-in intelligence) nature. However, the tried and tested techniques associated with microsimulation provide ‘important statistical mechanisms that ensure the similarity of what it predicts and what is actually observed in the gathered data’ (p. 446), which can aid in guiding patterns of population evolution.

Wu and Birkin (2012) suggest that the combination of the two modelling approaches allows large-scale data to be processed using list processing power, as well as to identify the consequences of behaviours and policies at a macro scale through predefined transition rates, while also modelling interactions and behaviours of individuals. Their mortality model demonstrated the importance of personal histories, with previous places of residence influencing health regardless of certain individual’s current residences, showing that ABMs can ‘complement MSM [microsimulation] by retrieving personal histories with great ease’ (p. 356). Given the potential shown by these models it is surprising that this approach has not been used more often.

Cajka et al. (2010) further demonstrated the benefit of combining microsimulation data with agent-based models, commenting that ‘although these models [ABMs] can simulate the realistic propagation of epidemics, they require input data about the social networks that are part of the agents’ day-to-day activities’ (p. 1). Although not modelling the spread of diseases, the paper demonstrates how personal attribute data agents from a microsimulation dataset can be used ‘to create school, workplace, and public transit interactions and then code this information into the data’ (p. 1), in attempting to build realistic social networks into interactive disease modelling.

The analysis of travel activity is another area where there has been considerable applied work aimed at combining spatial microsimulation and agent-based models and where there is great potential for further research. Miller (2018, this volume) offers an excellent overview of the state-of-the-art and presents the key issues and challenges as well as a research agenda.

Overall there is great potential for further applications of agent-based models for both longitudinal and historical analyses in a wide range of fields. The incorporation of interactions gives the method a different focus to spatial microsimulation modelling, while also demonstrating incredible adaptability in their set up. This includes connecting with other model types, incorporating other datasets, allowing them to 'borrow' the strength of these. The ability to base models on theory (for example, Cerda et al. 2014) also offers the exciting prospect of simulating conceptually valid and relevant studies. This theoretical grounding will be important for work to avoid being simply designated as 'blue skies research'. Despite all this, research combining multiple models within an urban environment backed by a specific theory is rare. Many studies have used hypothetical data in their analyses, so the opportunity to impute a representative population into a model using spatial microsimulation has huge potential for applied geographical analysis.

5 Concluding Comments

> Governments need to predict the outcomes of their actions and produce forecasts at the local level.
>
> (Openshaw 1995: 60)

It has long been anticipated that GIS-based simulation with the use of powerful computing and software will provide an enabling environment for comprehensive analysis of the impacts of government policy at different levels (including small area level). Significant progress in this direction has materialised with the rapidly expanding use of GIS in the Social Sciences (Ballas et al. 2017). It can be argued that, to some extent, this is due to the use of spatial microsimulation models and, to a lesser extent, of agent-based models. A key argument of this chapter is that the combination of spatial microsimulation and agent-based models has huge potential for the analysis of the short- and long-term impacts of social, regional, and urban policies upon different geographical areas and population segments. Furthermore, there is great potential to combine the two approaches to model all sub-systems that make up a local and regional socio-economic system, making the most of data on local labour market linkages, retail outlets, schools, hospitals, health services, etc. In particular, it is increasingly possible to build agent-based and spatial microsimulation models linking all datasets on the sub-systems that make up the local economy. For instance, data sources for groceries could be explored and the relevant database could be built, with the prospect of linking it to the household micro-database. Likewise, similar databases can be built for all existing hospitals, schools and major employers. An example of a set of specific aims and objectives that could be formulated in order to combine the approaches reviewed in this chapter and perform comprehensive spatial microsimulation and agent-based modelling can be summarised as follows:

- Develop a geographic synthetic micro-database of households and individuals using data from social surveys and small area data
- Estimate a geographic database of retail outlets. This could include actual or estimated floorspace and trading intensity, estimated attractiveness of the retailer, etc.
- Construct a database of amenities including schools, hospitals and health centres but also entertainment and recreation outlets (e.g. museums, theatres, cinemas but also spaces to socialise, bars, restaurants,)
- Build a database of transport networks and estimated trips (such as travel to work, travel to shop,)
- Link all these databases in order to explore the geography of quality of life in cities and regions—for example, link households to retail outlets using shopping flow data to see how well served different households are in different neighbourhoods for basic service provision.
- Use the spatial microsimulation outputs as a basis for agent-based models, representing the types of people that live in particular neighbourhoods, as well as the features and characteristics they would encounter in everyday life.
- Convert all micro-units to agents and model suitable interactions between them, including social interactions between agents, as well as family structures, and demographic turnover over the course of the model.
- Perform static *what-if* scenario analysis: i.e. answer questions such as ‘what if the patterns of service provision change?’
- Perform dynamic analysis into the future, including interactions between sub-systems that make up urban and regional systems and micro-units (defined as agents).

This list is by no means exhaustive. It just gives a flavour of the huge potential that there is for applying agent-based spatial microsimulation in a wide range of inter-disciplinary thematic contexts.

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