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Everything you need to know about agent-based modelling and simulation

CM Macal[1,2]*

[1]Argonne National Laboratory, Argonne, IL, USA; and [2]University of Chicago Computation Institute, Chicago, IL, USA

This paper addresses the background and current state of the field of agent-based modelling and simulation (ABMS). It revisits the issue of what ABMS represents as a new development, considering the extremes of being an overhyped fad, doomed to disappear, or a revolutionary development, shifting fundamental paradigms of how research is conducted. This paper identifies key ABMS resources, publications, and communities. It also proposes several complementary definitions for ABMS, based on practice, intended to establish a common vocabulary for understanding ABMS, which seems to be lacking. It concludes by suggesting research challenges for ABMS to advance and realize its potential in the coming years.
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Keywords: agent-based modeling and simulation; multi-agent system; modeling human behavior; computational social simulation

1. Introduction

The number and breadth of applications for agent-based modelling and simulation (ABMS) are truly remarkable, and continue to grow. Applications range across virtually all disciplines in the natural, social, and physical sciences as well as engineered systems and well beyond the usual ones for simulation in engineering, business, operations management, and similar fields (Macal and North, 2010, 2014). A recent 2-week period alone yielded new publications on agent-based models and multi-agent systems (MAS) on such diverse topics as modelling the nuclear fuel cycle (Huff *et al*, 2016), national culture and innovation diffusion (Desmarchelier and Fang, 2016), consensus analysis (Li *et al*, 2016), ‘flock’ leadership (Will, 2016), domestic water demand (Koutiva and Makropoulos, 2016), performance risk of construction contractors (Asgari *et al*, 2016), cooperative energy dispatch on microgrids (Fang *et al*, 2016), classroom evacuation (Liu *et al*, 2016), subway station evacuation (Li *et al*, 2016), and passenger terminal safety (Yatskiv *et al*, 2016).

Yet, the nature of ABMS—in terms of its essential characteristics, the development methods for constructing models, the relationship of ABMS with other types of simulation and modelling techniques, and so on—is far from generally understood or accepted. This is because, in part, of the myriad, diverse communities, who use the ABMS approach in their research and development applications.

In addition to the diversity of communities, there is a diversity of views on what ABMS is within and across communities, as well as by those outside the field of simulation, who may not use ABMS but are aware of its existence. Many regard ABMS as a distinct simulation and modelling technique, having characteristics and capabilities in addition to the standard simulation techniques of discrete-event simulation (DES) (Law, 2014), system dynamics (SD) (Richardson, 2009), Monte Carlo simulation (Rubinstein and Kroese, 2008), continuous simulation (Cellier and Kofman, 2006), and even combined DES/continuous simulation (Zeigler *et al*, 2000). From this view, ABMS is a separate topic that deserves special attention such as new curriculum development and new toolkits devoted to ABMS. Others regard ABMS as nothing new at all, and simply a disguised form of standard simulation methods, regarding ABMS, for example, as a subset of DES, or regard ABMS as no more than an alternative modelling approach to achieve exactly the same results that could be achieved using SD, for example. Both perspectives have proponents who argue their positions effectively. Still, many others continue to come into the field of ABMS having virtually no background in simulation because of their desire to solve important problems that have not been previously solved through any other simulation methods. Therefore, what does this apparent lack of consensus mean for ABMS and for its future?

Is there anything new or perhaps even ‘revolutionary’ about ABMS? Does ABMS represent a shift in fundamental paradigms of the field akin to a scientific revolution (Kuhn, 2012)? And where might ABMS be going in the future? Is ABMS merely a fad, doomed to disappear as many overhyped techniques have done, at best to be subsumed into existing tried-and-true modelling and simulation methods, and tools? Or does ABMS have a bright future, worthy of investment of one’s research career?

This paper begins to address these questions. Section 2 examines the background and current state of ABMS, providing links to the various disciplines and communities engaged in ABMS research and applications. Section 3 proposes several

**Correspondence: CM Macal, Global Security Sciences Division, Argonne National Laboratory, 9700 S. Cass Avenue, Building 221, Argonne, IL 60439, USA.*
E-mail: macal@anl.gov

definitions of ABMS, intended to establish a common vocabulary for ABMS, which seems to be lacking, with the hope of promoting progress in the field. Section 4 proposes areas for ABMS research necessary to advance the field in the coming years. The summary and conclusions section encapsulates the main results and their implications.

2. The phenomenon of ABMS

2.1. ABMS hopes

In the course of developing many agent-based simulation applications, I have been approached by potential research collaborators and clients who are interested in developing agent-based simulations. A common refrain is: 'We do not know what agent-based modeling is, … but we know we need it!'. Although people may not know the details of agent-based modelling, they seem to have the following:

1. An intuitive sense of what agent-based modelling is.
2. A recognition of the value of modelling populations of individual agents, which immediately necessitates the need to model the agents' behaviours and interactions.
3. A notion that the ABMS approach could lead to new insights and knowledge about the system of study, which are not easily available by using other simulation and modelling techniques.

Human behaviours, reactions, and interactions have been the missing element in descriptive models of the important systems that people urgently would like to model, forecast or predict, and test interventions upon.

There is something special about ABMS that seems to set it apart from other simulation and modelling techniques. Some of the unique characteristics of ABMS when viewed as a field of research include the following:

1. It cuts across many fields, seemingly embracing most, if not, all disciplines.
2. It draws people to it who have never had any experience with simulation.
3. It appears to present unique challenges in learning 'how to do ABMS', compared with standard simulation methods, thus the need for revising simulation and modelling curricula.
4. Existing software platforms (eg, DES packages) do not appear to be adequate for facilitating ABMS development, thus the need for a new set of dedicated ABMS tools.

The most important and distinguishing feature of ABMS is the *agent perspective* that is taken when viewing any system as consisting of agents. This is in contrast to the emphasis of DES models that focus on process or activity as the fundamental simulation element around which the models are constructed. In ABMS, the fundamental modelling construct is the agent and its behaviours, behaviours that affect the agent's own actions, the actions of other agents and the environment. In this regard, the agents' environment can very well include the processes and activities typically modelled by DES, and, thus, an ABMS model can subsume all logical components of a DES model, as well as much more. If we regard agent-based modelling as an organizing principle that informs us of both how to view a real-world system and how to effectively build a model of that system, then in practice, ABMS represents something unique and quite useful. ABMS offers a new perspective on thinking about and modelling systems that we always wanted to model well, but were not able to do so. ABMS is a bottom-up approach, whereas, it can be argued that, SD and DES are top-down approaches to modelling systems.

Yet the agent perspective is nothing new. Each of us is an agent in our daily actions and interactions with the real world, and we are already agent-based modellers in the sense that we are constantly choosing our own behaviours and anticipating the behaviours of others. Gabel (2003) argues that Aristotle was the first agent-based modeller, having devoted a treatise, *Poetics*, to simulations: what they are, how they differ from other products of the mind, and what the standards are for evaluating them (McKeon, 1973). Aristotle's analysis was of how the human propensity to imitate what we observe can eventuate in complex symbolic simulations. The simulations Aristotle had in mind were, of course, ancient Greek dramas.

The motivation for ABMS is the desire to model the world around us in a way that is more faithful to the real world. We desire to produce a model whose results are more or less in a one-to-one correspondence with the real world so that the jump in explanation from model to real world referent is minimal and convincing. People (agents) and social interactions and social processes are essential components of the systems in which we live, and in which we are concerned with—and ABMS, because it provides an explicit framework for modelling behaviour and interactions, is the leading method to model people, organizations, and societies. Axtell (2000) argues that ABMS provides unique kinds of information that are not available from any other modelling approach. From this perspective, ABMS is an applications motivated discipline. Yet, there is a famous quote, 'modeling for insights, not numbers', that comes to mind (Huntington *et al*, 1982). There are many applications of ABMS that simply create insights that can be valuable information to support decision-making—that is, the right information supplied at the right time.

Another motivation for ABMS is to advance science directly and to either test or develop new theories. Some have said that ABMS is a third way of doing science (Axelrod, 2003) in addition to inductive and deductive processes. Epstein (2006) argues that the ability to grow artificial societies using ABMS holds out the prospect of a new, *generative*, kind of social science. ABMS offers a method of implementing causal processes and mechanisms in a model not only to determine the implications of theory (strengths, inconsistencies, deficiencies) but also to provide a basis for obtaining causal explanations of modelled phenomena.

What words best describe the phenomenon of agent-based modelling? Is ABMS just another simulation method ultimately to be relegated to the toolbox of arcane modelling techniques, a boutique simulation technique of interest only to simulation modellers and analysts? Is the current attractiveness of ABMS of fleeting interest to the simulation community, propelled by hyperbolized claims for how ABMS will (or perhaps could, might, etc) impact the world? Or is ABMS something very different perhaps—a 'scientific revolution', in the sense of Kuhn (2012) in that ABMS represents a paradigm shift that could change the course of research and applications in the field of simulation?

Can a new simulation technique be revolutionary? The question has been asked before. Bankes (2002) notes that, 'there are numerous precedents in history of a new tool catalyzing revolutionary developments in the science that used that tool', and goes on to give several examples from the history of science. Bankes (2002) cites the reasons for the potential importance of ABMS as 'the unsuitability of competing modeling formalisms to address the problems of social science, agents as a natural ontology for many social problems, and emergence'. Axtell (2000) argues there are distinct uses of ABMS that offer significant benefits over standard analytical models. Resorting to agent-based modelling 'may be the only way to explore such processes systematically and can shed significant light on the solution structure, illustrate dynamical properties of the model, serve to test the dependence of results on parameters and assumptions, and be a source of counter-examples' (Axtell, 2000). Bankes (2002) concluded that indeed ABMS is a revolution in progress, although more of a promise of what ABMS could accomplish than a realized potential. In any case, ABMS has grown in several different research communities spanning a variety of scientific and application domains.

2.2. ABMS communities

The history of ABMS has been a rich one for at least 40 years, depending on what you consider to be the seminal developments leading to the field (see Heath, 2010; Heath and Hill, 2010; Wilensky and Rand, 2015 for many details on the history of ABMS and insights into its emergence as a field). Some well-cited introductory material on ABMS includes Axelrod and Tesfatsion (2016), Bonabeau (2001), Gilbert (2008), Gilbert and Troitzsch (2005), Helbing and Balietti (2011), Railsback and Grimm (2011), Wilensky and Rand (2015), and North and Macal (2007).

The last 20 years have seen a continuous stream of new agent-based modelling applications, methods, and theory, propelled, at least in part, by the publication of the book *Growing Artificial Societies* (Epstein and Axtell, 1996) and the release of the first agent-based modelling toolkit, *Swarm*, by Chris Langton and others at the Santa Fe Institute (Minar *et al*, 1996). New simulation software languages and tools specifically focussed on ABMS development have become established as open-source ABMS platforms, such as NetLogo (Wilensky and Rand, 2015; NetLogo, 2016), Repast (North *et al*, 2013; Repast, 2016), and MASON (Luke *et al*, 2005; MASON, 2016), and as commercial products such as AnyLogic (Borshchev, 2013; AnyLogic, 2016). DES software is evolving to incorporate agent-based simulation capabilities (Simio, 2014).

A variety of communities are engaged in ABMS work, many outside the traditional field of computer simulation. Several ABMS research traditions developed, often independently, in various fields and disciplines: social science; economics; geography; ecology; cognitive, behavioural, and organizational sciences; complexity science, including complex adaptive systems (CAS) and A-Life (Artificial Life); and cellular automata.

Agent-based models have been developed to study social phenomena and to demonstrate how such models could aid in the development of social theory. Schelling's segregation model, which was originally not implemented as a computational model, defined social interaction patterns for agents located in cells on a grid, literally on a checkerboard (Sakoda, 1971; Schelling, 1971). Schelling demonstrated how individuals acting according to their own micro-level rules of social behaviour and interaction could produce 'emergent' patterns at the macro level that were unexpected, not easily predictable, and not amenable to treatment by analytical means. These emergent effects were because of the non-linearities in the agent behaviours and social relationships, thus necessitating some form of computation for solution of the model (Schelling, 1978). Similarly, Axelrod's (1984) Tit-for-Tat model was an early social simulation that modelled individuals who interacted in local neighbourhoods. Axelrod demonstrated how cooperation among competing agents could spontaneously emerge. These agent-social interaction spaces were reminiscent of the cells and interaction patterns of cellular automata, with cells, grids, local von Neumann neighbourhoods, stationary agents located in cells having behavioural rules, and so on, as the primary constructs. Epstein and Axtell (1996) provided a comprehensive approach for using ABMS as an experimental platform for understanding social processes, as well as for building social science theory, through the simulation of entire artificial societies. Using mobile social agents moving on grids and establishing neighbours through proximity, as well as connected via networks, Epstein and Axtell were able to produce many results and patterns suggestive of real-world social processes and emergent societal patterns.

What ABMS brings to social simulation is a framework for explicitly specifying causal mechanisms, whether they are models of individual behaviour or social interaction that underlies models of society. Epstein (2006) has termed this approach Generative Social Science. The social simulation community, and more broadly the computational social science field that encompasses social network analysis and other analytical and computational techniques, continues to thrive and be a source of innovation for the ABMS field (Gilbert and Troitzsch, 2005; Gilbert, 2008; Squazzoni, 2012; Cioffi-Revilla, 2014; Conte and Paolucci, 2014). Many ABMS papers are published in the *Journal of Artificial Societies and Social Simulation* (*JASSS*, 2016), *Social Science Computing Review* (*SSCR*, 2016), *Computational and Mathematical Organization Theory* (*CMOT*, 2016), and other journals.

Economics offers a promising area for the application of ABMS because the standard assumptions of microeconomic theory (eg, perfect rationality, homogeneity, decreasing returns to scale, perfect and symmetric information, specified organizational forms and connectivity, and the long-run equilibrium state of the system is of primary interest), which are learned in any freshman microeconomics course, can be individually relaxed in ABMS. ABMS, because it does not make these restrictions, can be used to understand the importance of each simplifying assumption, and tested to see the effect of dispensing with the simplifying assumption in producing more accurate economic forecasts. The 2008 economic crisis caused a re-evaluation of the state of economic modelling, identifying shortfalls, and leading to proposals that ABMS might be able to offer some solutions. The failure of the then existing economic models to predict, or even suggest, the possibility of an impending economic crisis was something of a crisis in itself for the field of economic forecasting. The credibility and utility of such models were widely questioned. Farmer and Foley (2009) argued, 'Agent-based models potentially present a way to model the financial economy as a complex system, … while taking human adaptation and learning into account'. *The Economist* (2010) asked whether ABMS could do better than 'conventional' models in such situations. The agent-based economics modelling community continues to grow and be a source of innovation for the ABMS field. The Agent-based Computational Economics website (Agent-based computational economics (ACE), 2016) has many resources.

The cognitive, behavioural, and organizational sciences also have ongoing research threads that involve ABMS (Sun, 2006; Best *et al*, 2015), some of which are focussed on modelling human behaviour that is directly of interest to ABMS.

The early ABMS work in ecology was motivated to answer open questions that required modelling diversity of populations of organisms and species in such structures as food and energy webs (DeAngelis and Gross, 1992). The term used in the ecological modelling community to describe these models was individual-based model (IBM), referring to autonomous organisms in favour of the more general term 'agent'. A recent literature traces this early history of IBM in ecology (Railsback and Grimm, 2011). The ecological modelling community continues to be a source of innovation for the ABMS field, and many ABMS papers are published in the journals *Ecological Modeling* (*EM*, 2016), *Environmental Modeling and Software* (*EMS*, 2016), and others.

Combining ABMS with geospatial modelling and geographical information systems opens up new application areas for ABMS that have a strong geography component, such as modelling cities and urban environments (Heppenstall *et al*, 2016), humanitarian assistance (Crooks and Wise, 2013), and even contemporary issues such as border security (Latek *et al*, 2012).

ABMS is also inspired, in part, by the field of CAS, which has a foundational precept that systems are built from the 'bottom-up' and system properties emerge from individual autonomous entities (agents) and their interactions. This is in contrast to the 'top-down' view often taken in SD modelling in which a system is broken down into its constituent level components, successively if needed to be, until the appropriate level of fidelity has been achieved for a specific modelling purpose. Many early agent-based models took the form of cellular automata, consisting basically of a two-dimensional (2D) grid or lattice composed of cells in which each cell assumes one of a finite number of states at any point in time, on the basis of simple rules for cell 'behaviours'. Conway's 'Game of Life' is considered by some to be a simple agent-based model (Gardner, 1970). *Swarm* was inspired by A-Life applications modelled after cellular automata (Langton, 1986; Macal, 2009). In 1967, the programming language Logo was introduced, for educational purposes, with its notions of 'patches' and 'turtles', representing 'agents' visually moving over a 2D grid (Harvey, 1997). These constructs have led to many other Logo dialects, including NetLogo (2016). The early ABMS toolkits adopted this grid structure and eventually expanded it to include other topologies for agent interactions, including networks, n-dimensional spaces, a-spatial mixing, and so on.

Table 1 Sampling of publications introducing ABMS to disciplines

Discipline	*Key references*
Supply chains	Chen *et al* (2013), Swaminathan *et al* (1998)
Intelligent/distributed manufacturing	Leita (2009), Monostoria *et al* (2006), Shen and Norrie (1999)
Queueing	Sankaranarayanan (2011)
Economics	Hamill and Gilbert (2016), Farmer and Foley (2009), Tesfatsion and Judd (2006)
Finance	Bookstaber (2012), LeBaron (2005)
R&D (Pharmaceuticals)	Hunt *et al* (2013)
Marketing	Rand and Rust (2011)
Tourism	Nicholls *et al* (2016)
Environmental planning and policy	Zellner (2008)
Land use	Parker *et al* (2003)
Urban/architecture	An (2012)
Transportation	Bernhardt (2013)
Geography, geospatial analysis	Heppenstall *et al* (2012), Crooks and Heppenstall (2012), Crooks *et al* (2008)
Cognitive science	Bedau (2003)
Psychology	Smith and Conrey (2007)
Archaeology	Cegielski and Rogers (2016), Wurzer *et al* (2015), Lake (2014)
Healthcare	Maglio *et al* (2014), Luke and Stamatakis (2012)
Epidemiology/ infectious diseases	Auchincloss and Diez Roux (2008), Epstein (2009)

Table 1 provides some well-cited introductory material introducing ABMS in a sampling of disciplines and research areas. These publications include state-of-the-art surveys and overviews, and serve as entry points into ABMS using the language and constructs of the discipline. They introduce ABMS concepts and approaches, reference key resources, provide simple illustrative models in some cases, discuss the potential of ABMS for advancing specific fields, and indicate how to get started in developing ABMSs. These types of publications are strewn across the technical literature, and are often hard to locate for those outside the discipline.

2.3. ABMS communities of communities

An important challenge for ABMS is how to capitalize on the diversity of disciplines that is rapidly pushing forward on ABMS developments, recognizing that researchers who have established themselves in their fields are not about to leave their disciplines to establish a new discipline devoted solely to ABMS. Establishing communities of ABMS is an approach that has been attempted, with mixed results. The Network for Computational Modelling for SocioEcological Science (CoMSES Net) is a scientific research coordination network, which has sustained itself, to support and expand the development and use of computational modelling in the social and life sciences. OpenABM (http://www.openABM.org) is a node in the CoMSES Network, providing a growing collection of tutorials and FAQs on agent-based modelling, a model library intended to provide a locus for authors and modellers to share their models, and forums for modelling-related discussions and job postings. The OpenABM website includes a Computational Model Library, educational resources, a bibliographic library, and active forums on ABMS.

Annual conferences devoted to agent-based modelling have become sustained, mainstream professional activities. Traditional conferences such as the Winter Simulation Conference (WSC), Summer Sim, Spring Sim, and several others have added tracks to their conferences devoted to ABMS, and these appear to be sustainable. Hardly an issue of a simulation journal today does not include at least one article on ABMS theory, methods, or applications. Listserves devoted to the subject, such as SIMSOC and ComSES Digest, provide a continuous online source of ABMS advice, guidance, resources, and forum for advancing the state-of-the art of ABMS.

2.4. ABMS trends

Agent-based modelling is closely related to the field of MAS (Uhrmacher and Weyns, 2009). People often ask what the difference is between ABMS and MAS. There is not a clear distinction between agent-based modelling and MAS. Many papers in the literature seem to use the terms synonymously, and thus the difficulty in determining current trends in ABMS and MAS. MAS has an earlier history than agent-based modelling, aligned with robotics and artificial intelligence (AI), at least the decentralized sort of AI. Coming from the MAS literature, Jennings (2000) provides a computer science view of agency emphasizing the essential characteristic of autonomous behaviour, just as in ABMS.

Engineering design was the goal of much MAS research including the design of robotic systems and, specifically, to identify the rules by which individual agents should operate to achieve a common goal. For example, a contemporary design challenge is how to design the behavioural rules for a swarm of UASs (unmanned autonomous systems) to maximize their coverage of a region and efficiently fuse their sensed information into a common operating picture. Designing the logic of autonomous agents deployed across an electric power microgrid is another application of agents to engineering design (Hernandez *et al*, 2015).

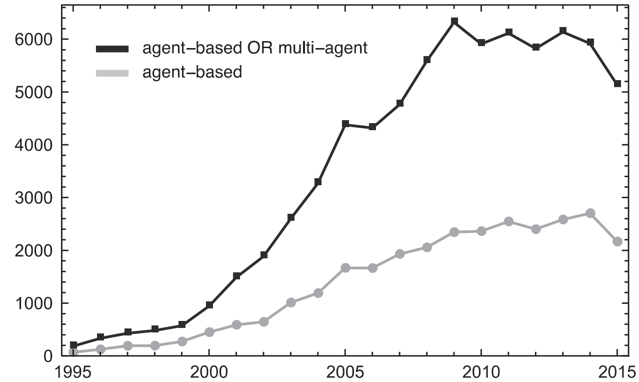

Figure 1 Trends in agent-based and multi-agent publications.

Engineering design is a normative discipline in that the challenge is how to develop the *best* design for a system, selecting from all possibilities. In contrast, agent-based modelling typically takes a descriptive perspective on systems: how to best describe how agents actually behave and interact for the purpose of understanding the emergence of social structures and organizations (Holland, 1997; Kaufman, 1993) or forecasting the future course of the system. Both the normative and descriptive motivations share the technical problem of understanding the link between the micro (rules of behaviour) and the macro (system-level behaviours). Both resort to computer computation of simulated, dynamic processes and interactions owing to the complexity of the problem and the lack of analytical means for deriving these relationships.

Much activity continues in ABMS. As of mid-February 2016, Scopus (http://www.scopus.com), the largest abstract and citation database of peer-reviewed literature, returned 29705 documents for 'agent-based' and 52206 documents for 'multi-agent', with an overlap of 8309 documents for the term 'agent-based' and 'multi-agent'. (Although this query was not a perfect match with what we are looking for, as it returns references to chemical or disease agents, the vast majority of publications returned refer to agent-based or multi-agent models, as desired.) Agent-based modelling as a field has exhibited steady growth from 1995 to 2010, judging by the number of publications in the field (Figure 1). Since 2010, Figure 1 shows a levelling off in the number of publications. Searches in the ACM Digital Library (http://dl.acm.org) and IEEE Xplore Digital Library (http://ieeexplore.ieee.org) yield very similar trends. More specific to the simulation field, a search of the WSC Proceedings since 2008, using the same keywords, returns 22–30% of the conference publications, with 30% (139 out of 473 publications) for the most recent WSC 2015.

In addition, the subject fields covered by the publications returned appear to cover virtually all the subject areas covered by the search engines, with the top areas being computer science, mathematics, engineering, social sciences, business, decision sciences, environmental science, and economics. Finally, the *Journal of Simulation* has published 29 papers referencing 'agent' in the past 10 years. The simulation journals *ACM Transactions on Modeling and Computer Simulation (TOMACS), Simulation: Transactions of the Society for Modeling and Simulation International, Simulation Modelling Practice and Theory*, and the *International Journal of Simulation and Process Modelling* regularly publish papers on ABMS.

3. Towards common definitions of ABMS

What is agent-based modelling? What is an agent? What is new and different about agent-based modelling? I am asked these questions often by people who come from many disciplines, some who have experience in ABMS modelling and many others who are new to the field, and would like to develop an agent-based model. There is no universal agreement on the precise definition of the term agent, or, by extension, on the term agent-based model (Macal and North, 2010).

What people refer to as an agent-based model can vary widely, and in important ways in terms of the details. It is not unusual for someone to claim that their model is agent-based only to have others take exception to that claim. For example, some claim their models are agent-based solely because they are object-oriented in their structure, or they are implemented using an agent-based modelling toolkit, or they have entities who have 'behaviours'. In this view, even models of physical systems such as those addressed by the specialized field of molecular dynamics, in which the agents consist of molecules, and their behaviours are the physical principles they adhere to. Perhaps these are as much agent-based models as they are any other type of model. But this classification may not be useful beyond the semantic distinction.

One way to proceed towards a precise definition of ABMS is to ask what most people think about when they use the term, as in what 'agent' suggests, even including those who have never done research involving agent-based modelling. Another avenue to defining ABMS is to consider what people who do agent-based modelling are actually referring to when they report their models. It is common for an agent-based model to be thought of as one composed of individual entities that have autonomous behaviours and are different from one another, having diverse characteristics and behaviours over a population.

Recognizing that a single definition of ABMS is unlikely to be universally accepted for a variety of reasons, I offer four alternative definitions of ABMS in increasing complexity, based on applications appearing in the literature. These definitions span what people tend to think of as ABMS. I have found these definitions very useful in communicating with modellers and policymakers alike, about the nature and capabilities of ABMS and its relationship to other modelling approaches. The definitions are informal at this point but are an essential area for future work.

Definition 1: An *individual ABMS* is one in which the agents in the model are represented individually and have diverse characteristics.

Many would say that the primary requirement for an agent is its representation as a distinct individual. In this view, the agent has the capability to act independently during the course of the simulation, but its behaviour can be scripted, that is, an agent can simply act on a time schedule, for example, and not have all of its behaviours be reactive to current events or its own endogenously determined internal state. This approach precludes the need for an agent to have an individual state. Early traffic simulations that modelled individual drivers in large metropolitan areas, such as TRANSIMS (Smith *et al*, 1995), took this approach to modelling drivers who followed a scripted schedule during which they travelled from origins to destinations, and interacted with other drivers on roadways. Such simulations are not reactive to new events as they occur during the simulation, such as road accidents or route interruptions. Recent ultra-large-scale population simulations have taken this approach also because of computational constraints.

Definition 2: An *autonomous ABMS* is one in which the individual agents have internal behaviors that allow them to be autonomous, able to sense whatever condition occurs within the model at any time, and to act on the appropriate behavior in response.

Many would say that the fundamental feature of an agent is autonomy, the capability for agents to make independent decisions based on the state of the system at any time and to act without direction provided by external guidance or prescription (Jennings, 2000). Representing an agent's reactive behaviours necessitates the need for an agent to have its own internal state upon which its behaviours can be based. An agent's internal state is implemented as a subset of the agent's defined characteristics that are updated dynamically during the course of the simulation at scheduled event times in which the agent behaviours are executed.

Some models emphasize agent individuality and autonomy, but the agents do not interact with each other. Such an approach is perfectly reasonable if, for example, a government organization is modelling the entire population of a country at an individual level for the purposes, say, of forecasting the earnings potential of workers, worker relocation patterns, and the amount of tax revenue that will be collected. Another example is of a healthcare insurance provider who is forecasting the health of the insured population using detailed models of the individuals' health and disease. In these kinds of models, which tend to be large-scale in nature and computationally intensive, the additional detail of including agent interactions would be of little benefit.

Table 2 Definitions for ABMS based on agent properties

ABMS definition/ agent properties	*Individuality*	*Behaviours*	*Interactions*	*Adaptability*	*Example*
Individual ABMS	Individual heterogeneous agents*	Prescribed, scripted†	Limited	None	Traffic model that has agents moving between origin–destination pairs according to a script
Autonomous ABMS	Individual heterogeneous agents*	Autonomous, dynamic‡	Limited	None	Taxation model in which agents choose occupations and places to work but do not interact with others
Interactive ABMS	Individual heterogeneous agents*	Autonomous, dynamic‡	Between other agents and the environment¶	None	Infectious disease model in which agents transmit and are infected through contact and respond to their disease state according to prescribed behaviours
Adaptive ABMS	Individual heterogeneous agents*	Autonomous, dynamic‡	Between other agents and the environment	Agents change behaviours during the simulation‖	Healthcare model in which agents change their behaviours according to the state of their health

*Agents in the population have diverse set characteristics.
†Agent behaviour is exogenously provided and not based on endogenous events during the simulation.
‡Agent behaviour is endogenous based on the current agent state.
¶Agent behaviours are based on the observed states and behaviours of other agents and the state of the environment.
‖Agents change behaviours during the simulation, agents learn, and/or populations adjust their composition.

Definition 3: An *interactive ABMS* is one in which autonomous agents interact with other agents and with the environment.

The primary motivation for social simulation as described in Section 2 is to model the social interactions as well as behaviours of agents to understand how various social structures, institutions, and patterns emerge as a result. The vast majority of agent-based models have some form of dynamic interaction among agents and the environment. Examples include models in which information diffuses through a population, or an infection spreads through a population, because of agent contact. Including agent interactions in such a model introduces another degree of computational complexity related to agent coordination. Specialized algorithms are required for efficient implementation of large-scale interactive ABMS.

Definition 4: An *adaptive ABMS* is one in which the interacting, autonomous agents change their behaviors during the simulation, as agents learn, encounter novel situations, or as populations adjust their composition to include larger proportions of agents who have successfully adapted.

Others would say that the fundamental feature of an agent is its capability to adapt and change its behaviours. Adaptation may be a result of learning in which the agent 'remembers' previous encounters with various situations and remembers what the outcomes of its behaviours were in these situations. An agent does this by including that information into its internal agent state. Adaptation might also result as an agent creates a new behaviour when faced with a novel situation. An agent does this through behaviours that act on behaviours, or by an abstract behaviour model. Agent behaviours can reflect adaptive behaviour beyond simple rules that change rules, by representing agent behaviour using advanced algorithms, such as machine learning and genetic programing. Another form of adaptation can be implemented in ABMS at the population level, whereby individuals do not change their behaviours, but the composition of agents in the population adjusts over time to include larger proportions of agents that have successfully adapted.

In all of the four definitions above, an agent-based model is characterized by the properties of the agents in the model. Table 2 summarizes the definitions for ABMS based on these properties.

The distinctions between ABMS facilitated by the definitions above are useful in communicating about and understanding what a particular agent-based model is, what it does, how it works, and what it possibly could do. When encountering an agent-based model, one would want to ask how the agents in the model are treated in terms of the key notions of individuality, autonomy, interactivity, and adaptability.

The ABMS definitions above, although not mathematically precise, are useful in distinguishing ABMS from other modelling and analytical approaches. Agent-based modelling is attractive because it offers the capability to model a population of heterogeneous agents. For if agents were all assumed to be the same and a 'representative' agent could stand in for the population as a whole (as in the perfectly rational agent in economics), one could work with greatly simplified models, some possibly simple enough that they would be amenable to analytical treatment, and obviate the need to resort to resource-intense computations.

An example is distinguishing ABMS (as defined above) from SD modelling. SD models tend to aggregate agents with similar characteristics into homogeneous population compartments, which in practice tend to be few in number compared with the number of agents in the entire population, whereas ABMS emphasizes individuality and heterogeneity (Definition 1). It is also important to understand the distinction between ABMS and swarm optimization algorithms, such as ant colony optimization and particle swarm optimization. Swarm optimization, from the field of bio-inspired evolutionary algorithms (Olariu and Zomaya, 2006), has been used to solve practical, large-scale optimization problems (Bonabeau *et al*, 1999; Barbati *et al*, 2011). The basic idea is that multiple agents search a landscape and interact by sharing information directly with other agents, or indirectly by using the environment as a medium in a process called *stigmergy*. The agents are continually acting on that information and executing behaviours in such a way that flocks or herds of agents emerge and converge on, at least locally, optimal solutions. Agents can recall past search paths from their memories to avoid repeating previous paths and even convey this information to other agents as well so that a collective picture of the landscape emerges.

If each agent in an agent-based model has an internal state and interacts with other agents and the environment (per Definition 3, is an *interactive ABMS*), it admits the possibility of models that are agent-based but technically are not simulations in the usual sense—no processes or set of activities corresponding to the real world are being simulated. There is no time-stamping of events, and there is no simulation clock. An event consists of an agent executing its behaviours and interacting with other agents and the environment. There is a sequence of events, but the scalar ordering of events is, as time-stamping would provide, not present, *a priori*. In this case the sequence of events (ie, agent behaviours and interactions) can be dynamically generated, on the basis of the conditions within the simulation at a particular time. For example, agents needing or requesting more attention when searching a landscape may execute their behaviours and interactions more frequently. This is exactly how a swarm optimization algorithm proceeds, and one can argue the case that such swarm algorithms are fully agent-based models, if not necessarily simulations in the usual sense of the term.

The definitions of ABMS above are incomplete and fall short of being able to distinguish ABMS from other important techniques, such as DES and continuous simulation. To do this would require additional definitional machinery about event and time-advance mechanisms, a more precise definition of state, and so on, which are beyond the scope of the current paper. Distinguishing ABMS from other techniques is important to suggest not how ABMS can displace their use but more importantly how ABMS can be used in conjunction with them. This is one of the main future challenges for ABMS, as discussed in the next section.

4. The promise and challenges for ABMS

4.1. The promise of ABMS

'In the future virtually all computer simulations will be agent-based because of the naturalness of the agent representation and the close similarity of agent models to the predominant computational paradigm of object-oriented programming' (North and Macal, 2007). With the hindsight of the last 10 years, it is becoming clearer as to what the barriers are to adoption of ABMS if this potential is to become reality.

Bankes (2002) described the potential of ABMS early on when he wrote that a clear consensus among the papers in the Sackler Colloquium of the National Academy of Sciences (Sackler, 2001), which focussed on agent-based modelling, was that ABMS 'is a revolutionary development for social science', and suggested the challenges that needed to be met:

B1: Better treatment of uncertainty analysis.

B2: Calibration of models to data.

B3: Developing methodologies for using models to answer specific questions or to solve problems.

B4: Demonstrating emergent phenomena beyond simple computer graphics.

Heath *et al* (2009) considered ABMS practice by surveying 279 articles from 92 unique publication outlets. They identified improvements for advancing ABMS as an analysis tool:

H1: Development of specific tools that are independent of software.

H2: Development of ABMS as an independent discipline with a common language that extends across domains.

H3: Establishment of expectations for agent-based models that match their intended purposes.

H4: Requirement of complete descriptions of the simulation so others can independently replicate the results.

H5: Requirement that all models be completely validated.

H6: Developing applications of statistical and non-statistical validation techniques specifically for ABMS.

None of these challenges have been completely met at this point, but progress is being made on all of them. Many of these challenges (eg, B1, B2, B3, H1, and H3) pertain to better acceptance of simulation models and results in general, not only ABMS. But meeting the challenges may require solutions tailored to ABMS. For example, having agent-based models to be accepted by policymakers may be more difficult because the complexity of the models works against transparency and makes explanations of model output more time-consuming and difficult. Validation of agent-based models requires validating agent behaviours and emergent phenomena, in addition to system-level model outcomes (Hahn, 2013). Many early agent-based models were conceptual in nature, meant for illustration and theory construction. They were not calibrated to real-world data, were deterministic in nature, largely ignoring stochastic elements, and were not intended to provide results to policymakers or decision-makers. On many of these points, the field is evolving slowly, but steadily, with a trend to developing large-scale applications intended to provide information supporting policy analysis and decision-making. There is much promise for what agent-based modelling can accomplish, with many reasons to believe that it will realize its potential in addressing the tangible, immediate questions that decision-makers are actually concerned about (eg, Epstein, 2009; Farmer and Foley, 2009; Nature, 2009). Currently, there are few widely reported, documented cases of ABMS applications that have had direct policy impacts, or that are used on a regular basis as part of decision-making. Yet, even better ways for how ABMS could provide information to policymakers has become an area of research itself (Hoad and Watts, 2012).

To these suggestions, I would add the following challenges for ABMS as a field:

1. Increase *credibility* and trust in agent-based models and their results. A complex agent-based model can appear to be an unknown quantity compared with simpler, but accepted and established, modelling methods routinely used in a discipline. This situation can exacerbate the problem of having agent-based models and results published in mainstream journals. Better arguments are needed that articulate the justifiable need for, value of, and benefits gained from specific agent-based model applications.
2. Increase *transparency* in models, which is hindered by the complexity of agent-based models that makes results difficult to explain. Descriptions of models complete enough for others to independently replicate model results (addressing H4 above) would bring validated agent-based models closer to being instruments of scientific discovery. The Overview, Design Concepts, and Details (ODD) protocol is a significant step towards standardizing documentation and communications of agent-based models (Polhill *et al*, 2008; Grimm *et al*, 2010). Simulation journals are exploring review processes that include independent replication of models submitted for publication.
3. Expand *knowledge* of agent-based modelling to include: how agent-based models can be efficiently developed, how models can be effectively used to generate relevant information, and how to analyse and explain model results. Developing a well-defined body of knowledge about ABMS, and having a common language and definitions could help bridge disparate domains (partly addressing H2 above). Formal theories of ABMS will help define its capabilities and limitations (North, 2014). Lack of ABMS educational programmes for developing the next generation of researchers and facilitating researchers who want to immediately develop ABMS applications is holding the field back.
4. Increase the *ease-of-use* of tools for developing agent-based models. Agent-based modelling tools are continually being developed and upgraded with new capabilities, including making them easier to use. Lack of easy-to-use tools and standardized user interfaces for ABMS model development is a barrier to adoption of ABMS.

4.2. Some research challenges for ABMS

There are several research areas that show great promise for advancing the capabilities of ABMS to solve problems. A few of these research areas are described next.

Behavioural modelling. The behavioural modelling challenge for ABMS is to develop better representations of agent behaviour and the methods that populate behavioural models with the requisite data. One of the primary reasons that people are interested in ABMS is because they would like to include truer representations of human behaviour into their models or organizations and societies and see their collective effects. Advancements in behavioural economics and behavioural operations management have fuelled interest in better models of behaviour. Better models of agents are needed that describe how people actually behave in a variety of contexts. Agent-based models have moved beyond the normative rational actor model to include variations of the more descriptive bounded rationality model, in which agents' decisions and behaviours are tempered by realistic constraints on time, effort, and attention, among other approaches (Balke and Gilbert, 2014). Causative agent behavioural models based on insights from behavioural economics (Kahneman, 2011) and cognitive sciences (Sun, 2006) that include social and emotional factors could be essential elements of more predictive, and useful, agent-based models. For example, Epstein (2014) introduces a new theoretical entity, Agent_Zero, a conceptual software individual endowed with distinct emotional or affective, cognitive or deliberative, and social aspects, grounded in contemporary neuroscience that represents explicit causative factors underlying agent behaviours. New approaches using data analytics for inferring agent behaviours from data streams (Kosinaki *et al*, 2013) demonstrate how behavioural attributes can be identified from digital records. Data streams from social media and sensor networks offer the possibility of extracting agent behaviours in real time (Bengtsson *et al*, 2011) and dynamically aligning agent states to real populations. Robust behaviour models that can be continually calibrated and validated against real-world data would increase ABMS credibility.

Simulation analytics. The simulation analytics challenge for ABMS is to develop the methods and tools, such as data analytics and statistical analysis techniques, for extracting meaningful information from simulation results. ABMS's gain in complexity is at the loss of analytical tractability and the ability to derive facts *a priori* about agent-based models, such as relating micro-level agent behaviours to macro-level system outcomes. Instead, agent-based models must be simulated on a computer. Computational experiments must be cleverly designed in advance to efficiently obtain the data that can be used to understand model behaviours, sensitivities to parameters, and how uncertainties in input data and structural relationships (eg, agent behaviours) are propagated to model outputs. The problem is compounded in a stochastic environment by uncertain parameters characterized by ranges and distributions. A single run of a stochastic agent-based simulation consisting of millions of agents moving through an urban environment and updating their states hourly for a period of 10 years produces a terabyte of data. Doing many runs of a stochastic simulation or doing parameter explorations can require thousands of ensembles of simulations that can only be done in distributed computing environments and managed by specialized workflow software. In addition to the challenge of efficiently storing the model outputs in such a way that the data can be efficiently accessed, the challenge for large-scale data analytics is to extract key relationships embedded in the data. Data analytics approaches turned to simulation output data such as simulation analytics (Nelson, 2016) will be needed. In addition, new statistical methods and existing methods implemented for large-scale application of data analytics are needed to support agent-based modelling requirements (Thiele *et al*, 2014; ten Broeke *et al*, 2016).

Hybrid modelling. The hybrid modelling challenge is to understand how agent-based modelling can be effectively used with other simulation and modelling techniques operating together in the same 'hybrid' model in such a way that each technique addresses the part of the problem that it does best. Agent-based models need not be viewed as displacing other simulation techniques (Siebers *et al*, 2010). The ABMS/SD and ABM/DES combinations are the agent-related hybrid configurations that have received the most attention (Heath *et al*, 2011). The hybrid modelling challenge has both logical (how to link models together in a way that makes sense) and mechanistic elements (how to link two existing models together that use disparate modelling tools). An example of a hybrid model consists of an agent-based model of a regional economy, in which agents generate economic activity according to their detailed behavioural models, linked to a SD model that supplies the macroeconomic variables at the national level; the hybrid model captures the two-way linkages between the agent-based model and the SD model. ABMS toolkits have begun to incorporate hybrid-modelling capabilities.

Large-scale ABMS. The large-scale agent-based modelling challenge is to efficiently and effectively simulate large-scale agent-based models, consisting of millions of agents, at the city scale, or even billions of agents, at the global scale. The computing challenge is to develop algorithms and software for distributing agent-based models, or their interacting components, on high-performance computing, cloud computing, and other platforms (Collier *et al*, 2015). Research challenges include how to dynamically balance simulation workloads, interact with running simulations, and efficiently collect model outputs for further analysis. A large-scale ABMS challenge is to engineer processes for efficiently developing synthetic populations of agents, whether agents represent actual people, which comes with the associated data access and privacy issues, or only surrogate agents that correspond to the population, but only in the aggregate to properly address anonymity requirements.

5. Summary and conclusions

This paper has examined the current state of ABMS, providing background and links to the various disciplines and communities that conduct ABMS research and develop applications. Four definitions of ABMS were proposed based on the key features of agents typically included in such models: individuality, autonomy, interactivity, and adaptivity. The definitions were a start in establishing a footing for relating ABMS to other simulation and modelling techniques. Finally, I have suggested some research areas for ABMS in the next 10 years that will help this method realize its full potential.

A question posed at the beginning of the paper was whether there is anything new about ABMS: in considering that question, one is struck by the many parallels between how ABMS is advancing as a field and Kuhn's (2012) view that the shifting fundamental paradigms of a field are the hallmark of a scientific revolution. Noting that Kuhn also states that scientific revolutions occur at all scales, and a revolution in simulation may be a minor one as scientific revolutions go, the parallels are highly suggestive that ABMS represents a fundamentally new simulation and modelling technique that offers the potential to solve problems that are not robustly addressed by other methods.

Challenges remain if ABMS is to achieve its promise and realize its potential. One open challenge is whether the mechanisms can be developed and sustained for the various communities engaged in ABMS research to continue to share their developments as these individual fields advance and become more specialized in their use of ABMS. Positive developments towards achieving this aim include the expanding open access to the ABMS research literature, the indexing of the literature across its widely disparate research communities, and the ongoing publication of novel ABMS applications.

And finally, as to whether ABMS is a fad, doomed to an early extinction, the answer is that ABMS is alive and well, and the future is bright. Humans appear to be naturally motivated to model and simulate all of society, dating back to our earliest history, and only now, with the advent of powerful computers, is it possible to attempt to do so. Asimov (1988) provides a fanciful vision of where such possibilities could lead, when in a universe far into the future, scientist hero Hari Seldon invents the field of 'psychohistory', based on the recognition that society is composed of millions of autonomous interacting individuals, each making their own decisions. This enables him to precisely predict the behaviours of the course of society, but only in the aggregate and only if that information is kept highly secret. Undoubtedly, researchers in the foreseeable future will be compelled to explore and realize the possibilities for predicting the course of society and all of its parts, or prove that it cannot be done.

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References

Agent-based computational economics (ACE) (2016). http://www2.econ.iastate.edu/tesfatsi/ace.htm, accessed 31 January 2016.

An L (2012). Agent-based modeling in urban and architectural research: A brief literature review. *Ecological Modelling* **229**: 25–36.

AnyLogic (2016). http://www.anylogic.com/, accessed 27 February 2016.

Asgari S, Awwad R, Kandil A and Odeh I (2016). Impact of considering need for work and risk on performance of construction contractors: An agent-based approach. *Automation in Construction* **65**(May): 9–20.

Asimov I (1988). *Prelude to Foundation*. Doubleday: New York.

Auchincloss AH and Diez Roux AV (2008). A new tool for epidemiology: The usefulness of dynamic-agent models in understanding place effects on health. *American Journal of Epidemiology* **168**(1): 1–8.

Axelrod R (1984). *The Evolution of Cooperation*. Basic Books: New York.

Axelrod R (2003). Advancing the art of simulation in the social sciences. *Japanese Journal for Management Information Systems* **12**(3).

Axelrod R and Tesfatsion L (2016). On-line guide for newcomers to agent-based modeling in the social sciences, http://www2.econ.iastate.edu/tesfatsi/abmread.htm, accessed 14 February 2016.

Axtell R (2000). *Why agents? On the varied motivations for agent computing in the social sciences*. Working Paper 17. Center on Social and Economic Dynamics, Brookings Institution, Washington DC.

Balke T and Gilbert N (2014). How do agents make decisions? A survey. *Journal of Artificial Societies and Social Simulation* **17**(4): 13.

Bankes SC (2002). Agent-based modeling: A revolution? *Proceedings of the National Academy of Sciences* **99**(Suppl 3): 7199–7200.

Barbati M, Bruno G and Genovese A (2011). Applications of agent-based models for optimization problems: A literature review. *Expert Systems with Applications* **39**(5): 6020–6028.

Bedau MA (2003). Artificial life: Organization, adaptation, and complexity from the bottom up. *Trends in Cognitive Science* **7**: 505–512.

Bengtsson L, Lu X, Thorson A, Garfield R and von Schreeb J (2011). Improved response to disasters and outbreaks by tracking population movements with mobile phone network data: A post-earthquake geospatial study in Haiti. *PLoS Medicine* **8**(8): e1001083.

Bernhardt KLS (2013). Agent-based modeling in transportation. *70 Transportation Research Circular E-C113: Artificial Intelligence in Transportation* 72–80.

Best BJ, Kennedy WG and Amant St. R (2015). Behavioral representation in modeling and simulation: Introduction to CMOT special issue-BRiMS 2012. *Computational and Mathematical Organization Theory* **21**(3): 243–246.

Bonabeau E (2001). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences* **99**(3): 7280–7287.

Bonabeau E, Dorigo M and Theraulaz G (1999). *Swarm Intelligence: From Natural To Artificial Systems*. Oxford University Press: Oxford.

Bookstaber R (2012). *Using agent-based models for analyzing threats to financial stability*. Working Paper no. 0003 (21 December). U.S. Department Treasury. Office of Financial Research, https://financialresearch.gov/working-papers/, accessed 25 February 2016.

Borshchev A (2013). *The Big Book of Simulation Modeling: Multimethod Modeling with AnyLogic 6*. AnyLogic North America: Lisle, IL.

Cegielski WH and Rogers JD (2016). Rethinking the role of agent-based modeling in archaeology. *Journal of Anthropological Archaeology* **41**(March): 283–298.

Cellier FE and Kofman E (2006). *Continuous System Simulation*. Springer: New York.

Chen X, Ong Y-S, Tan P-S, Zhang N and Li Z (2013). Agent-based modeling and simulation for supply chain risk management—A survey of the state-of-the-art, *2013 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, Manchester, pp 1294–1299.

Cioffi-Revilla C (2014). *Introduction to Computational Social Science: Principles and Applications*. Springer: London.

Computational and Mathematical Organization Theory (CMOT) (2016). Springer, http://www.springer.com/new + %26 + forthcoming + titles + %28default%29/journal/10588.

Collier NT, Ozik J and Macal CM (2015). Large-scale ABM with RepastHPC: A case-study in parallelizing a distributed ABM. In: *PADABS 2015 Proceedings*. Vienna, Austria, 24–28 August.

Conte R and Paolucci M (2014). On agent-based modeling and computational social science. *Frontiers in Psychology* **5**: 668, http://doi.org/10.3389/fpsyg.2014.00668.

Crooks A, Castle C and Batty M (2008). Key challenges in agent-based modelling for geo-spatial simulation. *Computers, Environment and Urban Systems* **32**(6): 417–430.

Crooks AT and Heppenstall AJ (2012). Introduction to agent-based modelling. In: Heppenstall AJ, Crooks AT, See LM and Batty M (eds). *Agent-Based Models of Geographical Systems*. Springer: New York, pp 85–108.

Crooks AT and Wise S (2013). GIS and agent-based models for humanitarian assistance. *Computers, Environment and Urban Systems* **41**(September): 100–111.

DeAngelis DL and Gross LJ (1992). *Individual-Based Models and Approaches in Ecology: Populations, Communities, and Ecosystems*. Chapman and Hall: New York.

Desmarchelier B and Fang ES (2016). National culture and innovation diffusion. Exploratory insights from agent-based modeling. *Technological Forecasting and Social Change* **105**(April): 121–128.

The Economist (2010). Agents of change: Conventional models failed to foresee the economic crisis. Could agent-based modeling do better? 22 July (online), http://www.economist.com/node/16636121, accessed 15 February 2016.

Ecological Modeling (EM) (2016). Elsevier, http://www.journals.elsevier.com/ecological-modelling/.

Environmental Modeling and Software (EMS) (2016). Elsevier, http://www.journals.elsevier.com/environmental-modelling-and-software/.

Epstein JM (2006). *Generative Social Science: Studies in Agent-Based Computational Modeling*. Princeton University Press: Princeton, NJ.

Epstein JM (2009). Modelling to contain pandemics. *Nature* **460**(6): 687.

Epstein JM (2014). *Agent_Zero: Toward Neurocognitive Generative Social Science*. Princeton University Press: Princeton, NJ.

Epstein JM and Axtell R (1996). *Growing Artificial Societies: Social Science from the Bottom Up*. MIT Press: Cambridge, MA.

Fang X, Ma S, Yang Q and Zhang J (2016). Cooperative energy dispatch for multiple autonomous microgrids with distributed renewable sources and storages. *Energy* **99**: 48–57.

Farmer JD and Foley D (2009). The economy needs agent-based modeling. *Nature* **460**(7256): 685–686.

Gabel S (2003). Welcome. In: Macal, C, North M and Sallach D (eds). *Proceedings of Agent 2003 Conference on Challenges in Social Simulation*, 2–4 October, Chicago, IL, pp 151–152.

Gardner M (1970). The fantastic combinations of John Conway's new solitaire game 'life'. *Scientific American* **223**(October): 120–123.

Gilbert N. (2008). *Agent-Based Models*. Number 07-153. Sage: London.

Gilbert N and Troitzsch KG (2005). *Simulation for the Social Scientist*. 2nd edn, Open University Press: Maidenhead, UK.

Grimm V, Berger U, DeAngelis DL, Polhill JG, Giske J and Railsback SF (2010). The ODD protocol: A review and first update. *Ecological Modelling* **221**: 2760–2768.

Hahn HA (2013). The conundrum of verification and validation of social science-based models. *Procedia Computer Science* **16**: 878–887.

Hamill L and Gilbert N (2016). *Agent-Based Modelling in Economics*. John Wiley & Sons: New York.

Harvey B (1997). *Computer Science Logo Style*. MIT Press: Boston.

Heath BL (2010). *The history, philosophy and practice of agent-based modeling and the development of the conceptual model for simulation diagram.* PhD Dissertation, Department of Biomedical, Industrial and Human Factors Engineering, Wright State University.

Heath SK, Brailsford SC, Buss A and Macal CM (2011). Cross-paradigm simulation modeling: Challenges and successes, In: Jain S, Creasey RR, Himmelspach J, White KP, and Fu M (eds). *Proceedings of the 2011 Winter Simulation Conference*.

Heath BL and Hill RR (2010). Some insights into the emergence of agent-based modeling. *Journal of Simulation* **4**(3): 163–169.

Heath B, Hill R and Ciarallo F (2009). A survey of agent- based modeling practices (January 1998 to July 2008). *Journal of Artificial Societies and Social Simulation* **12**(4): 9.

Helbing D and Balietti S (2011). *How to do agent-based simulations in the future: From modeling social mechanisms to emergent phenomena and interactive systems design*, Santa Fe Institute working paper: 2011-06-024. Santa Fe, New Mexico, USA, http://www.santafe.edu/media/workingpapers/11-06-024.pdf.

Heppenstall AJ, Crooks AT, See LM and Batty M (eds). (2012). *Agent-Based Models of Geographical Systems*. Springer: Dordrecht.

Heppenstall A, Malleson N and Crooks AT (2016). 'Space, the final frontier': How good are agent-based models at simulating individuals and space in cities? *Systems* **4**(1): 9.

Hernandez L, Baladron C, Aguiar JM, Carro B, Sanchez-Esguevillas A and Lloret J (2015). Survey of multi-agent systems for microgrid control. *Engineering Applications of Artificial Intelligence* **45**(October): 192–203.

Hoad K and Watts C (2012). Are we there yet? Simulation modellers on what needs to be done to involve agent-based simulation in practical decision making. *Journal of Simulation* **6**(1): 67–70.

Holland J (1997). *Emergence: From Chaos to Order*. Addison—Wesley: Reading, MA.

Huff KD *et al* (2016). Fundamental concepts in the cyclus nuclear fuel cycle simulation framework. *Advances in Engineering Software* **94**(April): 46–59.

Hunt CA, Kennedy RC, Kim SHJ and Ropella GEP (2013). Agent-based modeling: A systematic assessment of use cases and requirements for enhancing pharmaceutical research and development productivity. *Systems Biology and Medicine* **5**(4): 461–480.

Huntington HG, Weyant JP and Sweeney JL (1982). Modeling for insights, not numbers: The experiences of the energy modeling forum. *OMEGA, The International Journal of Management Science* **5**(1): 449–462.

Journal of Artificial Societies and Social Simulation (JASSS) (2016). SimSoc Consortium, http://jasss.soc.surrey.ac.uk/JASSS.html.

Jennings NR (2000). On agent-based software engineering. *Artificial Intelligence* **117**(2): 277–296.

Kahneman D (2011). *Thinking, Fast and Slow*. Palgrave Macmillan: New York.

Kaufman SA (1993). *The Origins of Order*. Oxford University Press: Oxford.

Kosinaki M, Stillwell D and Graepel T (2013). Private records and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences* **110**(15): 5802–5805.

Koutiva I and Makropoulos C (2016). Modelling domestic water demand: An agent based approach. *Environmental Modelling & Software* **79**(May): 35–54.

Kuhn T (2012). *The Structure of Scientific Revolutions*. 4th edn, University of Chicago Press: Chicago: with postscript.

Lake MW (2014). Trends in archaeological simulation. *Journal of Archaeological Method and Theory* **21**(2): 258–287.

Langton CG (1986). Studying artificial life with cellular automata. *Physica D* **22**(1–3): 120–149.

Latek MM, Mussavi Rizi SM, Crooks AT and Fraser M (2012). A spatial multiagent model of border security for the Arizona-Sonora borderland. *The Computational Social Science Society of America Conference*, Santa Fe, NM, https://dl.dropboxusercontent.com/u/2696623/Website/CSSSA2012-1.pdf.

Law AM (2014). *Simulation Modeling and Analysis*. 5th edn, McGraw-Hill: New York.

LeBaron B (2005). Agent-based computational finance, http://people.brandeis.edu/~blebaron/wps/hbook.pdf, accessed 25 February 2016.

Leita P (2009). Agent-based distributed manufacturing control: A state-of-the-art survey. *Engineering Applications of Artificial Intelligence* **22**(2009): 979–991.

Li H, Chen G, Dong Z and Xia D (2016). Consensus analysis of multiagent systems with second-order nonlinear dynamics and general directed topology: An event-triggered scheme. *Information Sciences*. Available online 18 February, www.journals.elsevier.com/information-sciences.

Li Z-y, Tang M, Liang D and Zhao Z (2016). Numerical simulation of evacuation in a subway station. *Procedia Engineering* **135**: 615–620.

Liu R, Jiang D and Shi L (2016). Agent-based simulation of alternative classroom evacuation scenarios. *Frontiers of Architectural Research*. Available online 10 February, www.journals.elsevier.com/frontiers-of-architectural-research.

Luke S, Cioffi-Revilla C, Panait L, Sullivan K and Balan G (2005). MASON: A multiagent simulation environment. *Simulation* **81**(7): 517–527.

Luke DA and Stamatakis KA (2012). Systems science methods in public health: Dynamics, networks, and agents. *Annual Review of Public Health* **33**(April): 357–376.

Macal CM (2009). Agent based modeling and artificial life. In: Meyers R (ed.). *Encyclopedia of Complexity and Systems Science*. Springer: New York, pp 112–131.

Macal CM and North MJ (2010). Tutorial on agent-based modelling and simulation. *Journal of Simulation*. Special issue on agent-based modelling **4**(3): 151–162.

Macal CM and North MJ (2014). Introductory tutorial: Agent-based modeling and simulation, In: Tolk A, Diallo SD, Ryzhov IO, Yilmaz L, Buckley S, and Miller JA (eds). *Proceedings of the 2014 Winter Simulation Conference*, Savannah, Georgia, USA (7–10 December).

Maglio PP, Sepulveda M-J and Mabry PL (2014). Mainstreaming modeling and simulation to accelerate public health innovation. *American Journal of Public Health* **104**(7): 1181–1186.

MASON (2016). http://cs.gmu.edu/~eclab/projects/mason/, accessed 27 February 2016.

McKeon , R (ed). (1973). Introduction to Aristotle. In: *Aristotle, Poetics*. trans. I. Bywater. University of Chicago Press: Chicago.

Minar N, Burkhart R, Langton C and Askenazi M (1996). *The swarm simulation system, a toolkit for building multi-agent simulations*. Working Paper 96-06-042, Santa Fe Institute, Santa Fe, NM, http://www.santafe.edu/projects/swarm/overview/overview.html.

Monostoria L, Váncza J and Kumara SRT (2006). Agent-based systems for manufacturing. *CIRP Annals—Manufacturing Technology* **55**(2): 697–720.

Nature (2009). Editorial: A model approach. *Nature* **460**(6): 667.

Nelson BL (2016). 'Some tactical problems in digital simulation' for the next 10 years. *Journal of Simulation* **10**(1): 2–11.

NetLogo (2016). http://ccl.northwestern.edu/netlogo/, accessed 27 February 2016.

Nicholls S, Amelung B and Student J (2016). Agent-based modeling: A powerful tool for tourism researchers. *Journal of Travel Research*. Published online before print, 3 January. doi:10.1177/0047287515620490.

North M (2014). A theoretical formalism for analyzing agent-based models. *Complex Adaptive Systems Modeling* **2**(1): 3.

North MJ and Macal CM (2007). *Managing Business Complexity: Discovering Strategic Solutions with Agent-Based Modeling and Simulation*. Oxford University Press: Oxford, UK.

North MJ *et al* (2013). Complex adaptive systems modeling with repast simphony, *Complex Adaptive Systems Modeling*, Springer, Heidelberg, FRG, http://www.casmodeling.com/content/1/1/3.

Olariu S and Zomaya AY (2006). *Handbook of Bioinspired Algorithms and Applications*. CRC Press: Florida.

Parker DC, Manson SM, Janssen MA, Hoffmann MJ and Deadman P (2003). Multi-agent systems for the simulation of land-use and land-cover change: A review. *Annals of the Association of American Geographers* **93**(2): 314–337.

Polhill JG, Parker D, Brown D and Grimm V (2008). Using the ODD protocol for describing three agent-based social simulation models of land-use change. *Journal of Artificial Societies and Social Simulation* **11**.

Railsback SF and Grimm V (2011). *Agent-Based and Individual-Based Modeling: A Practical Introduction*. Princeton University Press: Princeton, NJ.

Rand WM and Rust RT (2011). Agent-based modeling in marketing: Guidelines for rigor. *International Journal of Research in Marketing,* **28**(3): 181–193

Repast (2016). http://repast.sourceforge.net/repast_simphony.php, accessed 27 February 2016.

Richardson GP (2009). System dynamics, The basic elements of. In:. *Encyclopedia of Complexity and Systems Science*. Springer, pp 8967–8974.

Rubinstein RY and Kroese DP (2008). *Simulation and the Monte Carlo Method*. 2nd edn. John Wiley & Sons: New York.

Sackler Colloquium (2001). Arthur M. Sackler colloquium of the national academy of sciences, *Adaptive Agents, Intelligence, and Emergent Human Organization: Capturing Complexity through Agent-Based Modeling*, held 4–6, October, at the Arnold and Mabel Beckman Center of the National Academies of Science and Engineering in Irvine, CA, http://www.pnas.org/content/99/suppl_3#ColloquiumPaper.

Sakoda JM (1971). The checkerboard model of social interaction. *Journal of Mathematical Sociology* **1**(1): 119–132.

Sankaranarayanan K (2011). *Study on behavioral patterns in queuing: Agent based modeling and experimental approach*, PhD Dissertation, Faculty of Economics, Institute of Management, Università della Svizzera Italiana (University of Lugano), October.

Schelling TC (1971). Dynamic models of segregation. *Journal of Mathematical Sociology* **1**(2): 143–186.

Schelling TC (1978). *MicroMotives and MacroBehavior*. Norton: New York.

Shen W and Norrie DH (1999). Agent-based systems for intelligent manufacturing: A state-of-the-art survey. *Knowledge and Information Systems* **1**(2): 129–156.

Siebers PO, Macal CM, Garnett J, Buxton D and Pidd M (2010). Discrete-event simulation is dead, long live agent-based simulation! *Journal of Simulation*. Special issue on agent-based modelling **4**(3): 204–210.

Simio (2014). http://www.simio.com, accessed 25 February 2016.

Smith L, Beckman R, Baggerly K, Anson D and Williams M (1995). TRANSIMS: TRansportation ANalysis and SIMulation system: Project summary and status, http://ntl.bts.gov/DOCS/466.html, accessed 27 February 2016.

Smith ER and Conrey FR (2007). Agent-based modeling: A new approach for theory building in social psychology. *Personality and Social Psychology Review* **11**(1): 87–104.

Squazzoni F (2012). *Agent-Based Computational Sociology*. John Wiley & Sons: Chichester, UK.

Social Science Computing Review (SSCR) (2016). Sage, http://ssc.sagepub.com/.

Sun R (2006). *Cognition and Multi-Agent Interaction: From Cognitive Modeling to Social Simulation*. Cambridge University Press: New York.

Swaminathan JM, Smith SF and Sadeh NM (1998). Modeling supply chain dynamics: A multiagent approach. *Decision Sciences* **29**(3): 607. ABI/INFORM Global.

Taylor SJE, Brailsford S, Chick SE, L'Ecuyer P, Macal CM and Nelson BL (2013). Modeling and simulation grand challenges: An OR/MS perspective, In: Pasupathy R, Kim S-H, Tolk A, Hill R and Kuhl ME, (eds). *Proceedings of the 2013 Winter Simulation Conference*, Washington DC, 8–11 December.

ten Broeke G, van Voorn G and Ligtenberg A (2016). Which sensitivity analysis method should I use for my agent-based model? *Journal of Artificial Societies and Social Simulation* **19**(1): 5.

Tesfatsion , L and Judd , KL (eds). (2006). *Handbook of Computational Economics, Volume II: Agent-Based Computational Economics*. Elsevier/North-Holland: Amsterdam: 904 pp.

Thiele JC, Kurth W and Grimm V (2014). Facilitating parameter estimation and sensitivity analysis of agent-based models: A cookbook using NetLogo and 'R'. *Journal of Artificial Societies and Social Simulation* **17**(3): 11.

Tolk A, Balci O, Combs CD, Fujimoto R, Macal CM and Nelson BL (2015). Do we need a national research agenda for modeling and simulation? In: Yilmaz L, Chan WKV, Moon I, Roeder TMK, Macal C, and Rossetti MD (eds). *Proceedings of the Winter Simulation Conference 2015*. Huntington Beach, CA, 6–9 December.

Uhrmacher AM and Weyns D (2009). *Multi-Agent Systems: Simulation and Applications*. CRC Press: Boca Raton, FL.

Wilensky U and Rand W (2015). *An Introduction to Agent-Based Modeling: Modeling Natural, Social and Engineered Complex Systems with NetLogo*. MIT Press: Cambridge, MA.

Will TE (2016). Flock leadership: Understanding and influencing emergent collective behavior. *The Leadership Quarterly*. Available online 15 February, www.journals.elsevier.com/the-leadership-quarterly.

Wurzer, G, Kowarik, K and Reschreiter, H (eds). (2015). *Agent-Based Modeling and Simulation in Archaeology*. Springer: New York.

Yatskiv (Jackiva) I, Savrasovs M, Gromule V and Zemljanikins V (2016). Passenger terminal safety: Simulation modelling as decision support tool. *Procedia Engineering* **134**: 459–468.

Zeigler BP, Praehofer H and Kim TG (2000). *Theory of Modeling and Simulation: Integrating Discrete Event and Continuous Complex Systems*. 2nd edn, Academic Press: San Diego, CA.

Zellner ML (2008). Embracing complexity and uncertainty: The potential of agent-based modeling for environmental planning and policy. *Planning Theory & Practice* **9**(4): 437–457.

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