
Editorial: Meeting Grand Challenges in Agent-Based Models

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Abstract: This editorial paper reviews the state of the science about agent-based modeling (ABM), pointing out the strengths and weaknesses of ABM. This paper also highlights several impending tasks that warrant special attention in order to improve the science and application of ABM: Modeling human decisions, ABM transparency and reusability, validation of ABM, ABM software and big data ABM, and ABM theories. Six innovative papers that are included in the special issue are summarized, and their connections to the ABM impending tasks are brought to attention. The authors hope that this special issue will help prioritize specific resources and activities in relation to ABM advances, leading to coordinated, joint efforts and initiatives to advance the science and technology behind ABM.

Keywords: Agent-Based Modeling, Complex Systems, System Integration, Social-Ecological Systems, Overview

Introduction

- 1.1 The use of agent-based models (ABMs)¹ has increased rapidly among various scientific communities over the last two decades. According to an online survey, the number of articles reporting the development or use of ABMs has been steadily increasing in an exponential rate since the mid-1990s, ranging across such research fields as ecology, epidemiology, human-environment science, land systems science, sociology, and political science (An et al. 2017).
- 1.2 This increasing interest in and use of ABMs is rooted in a set of challenges humans face: Virtually all major current challenges of humankind involve complex systems, such as economies, political and social-ecological systems or financial markets, comprised of autonomous, decision-making agents, including animals, people, families, parties, or companies. Due to their complexity, researchers cannot handle these systems in a controlled way common to science. We need models that understand the internal organization and processes of these systems sufficiently to address, for example, sudden regime shifts and collapse. Statistical and mathematical models cannot fully capture many key features of complex systems: agents, including non-human organisms and social groups, among others, are different in that they interact not globally but locally or within complex networks, and they adapt their behavior to the current state of themselves and their spatially and temporally varying environment. Agent-based modeling (ABM) can capture these aspects and has therefore become a widely used tool.

ABM Concept

- 2.1 Agent-based modeling (ABM), or individual based modeling (IBM, named so largely by ecologists), is rooted on the fundamental philosophy of methodological individualism, which focuses on the uniqueness of individuals

and interactions among them or between them and the associated environment(s). Technologically, agent-based modeling has emerged and prospered with the advent of increasingly available computing power and data and, a decade or so later, with the advent of object oriented programming and specific software packages for ABMs (Askenazi et al. 1996).

- 2.2 ABMs have intellectual origin from, and substantially contribute to, complexity science. Complexity science aims to understand complex systems, which often include heterogeneous subsystems, autonomous entities, nonlinear relationships, and multiple interactions among them (Arthur 1999; Axelrod et al. 2001; Crawford et al. 2005; Levin et al. 2013). ABM's basic paradigm of representing the entities and subsystems as agents (often at various, often hierarchical levels) and employing flexible rules to mimic many complex relationships and interactions — just satisfies the needs of understanding complex systems. Such systems feature path-dependence, self-organization, difficulty of prediction, and emergence that cannot be inferred from system components and their attributes alone (Banks 2002a; Manson 2001). Hence it is suggested that the ABM approach be employed to understand, harness, and improve (rather than fully control) the system's structure and function, taking innovative actions to steer the system in beneficial directions (Axelrod et al. 2001).
- 2.3 ABMs have witnessed increasing adoption when studying social systems, ecological systems, and social-ecological systems (Eliassen et al. 2016, 2009; Giske et al. 2014; Grimm et al. 2006). A range of empirical studies also show that many social-ecological systems manifest complexity features: heterogeneity, reciprocal effects and feedback loops, nonlinearity and thresholds, surprising outcomes (observable as a result of human-nature couplings), legacy effects and time lags, and resilience (An et al. 2017; Egli et al. 2019; Grimm & Railsback 2005; Liu et al. 2007; Zvoleff & An 2014).
- 2.4 ABM is capable of addressing these complexity-related challenges because of its intrinsic capacity to incorporate individual-level (e.g., heterogeneous subsystems, autonomous entities) information, to allow for multiple nonlinear relationships and interactions such as feedbacks, learning, and adaptation, to account for spatially and temporally variable information, and to integrate cross-scale and cross-discipline data and methods (An et al. 2005; National Research Council 2014). Another key value of ABM is the ability to represent human behavior more realistically by accounting for bounded rationality, heterogeneity, agent-agent and agent-environment interactions, evolutionary learning and adaptation, among others (An 2012; Filatova et al. 2013; Groeneveld et al. 2017; National Research Council 2014; Parker et al. 2003).
- 2.5 Since the NAS Sackler Colloquium addressing the topic in 2001 (Banks 2002a,b), agent-based modeling has made major advances in many areas, including the establishment of platforms supporting user-friendliness, diversity, usability, and available open-source resources (e.g., <https://www.comses.net/>). Because the ABM methodology explores dynamic paths, ABMs are especially useful when the processes under investigation involve abrupt changes, crises, and critical transitions related to social interactions and adaptive behavior, answering many “what-if” questions that shed light into the system's paths or trajectories under given conditions. Therefore, according to National Academy of Science, ABMs are useful at the intervention design stage because they provide a means for projecting possible effects of policies or decisions *ex ante* (National Research Council 2014).

ABM Challenge

- 3.1 Agent based models were greeted with enthusiasm initially (Banks 2002a; Huston et al. 1988), but this response faded quickly: “Scientists sometimes tend to rush to a new approach that promises to solve previously intractable problems, and then revert to familiar techniques as the unanticipated difficulties of the new approach are uncovered” (Grimm et al. 2005, p. xi). Critiques of ABMs asked for the identification of outcomes that differ from or are better than other types of models and for validation of ABMs. Interestingly, such responses are not always asked of other, non-ABM model types. A number of difficulties (many of them are common to any type of modeling, not necessarily unique to ABM), in turn, may account for, at least partially account for, some hesitance, misuse, misunderstanding, or doubt about ABM (Couclelis 2002; Roughgarden 2012).
- 3.2 A number of challenges regarding ABM still warrant in-depth exploration and research, however, including difficulties in communication of ABMs due to lack of common standards or protocols (with a few exceptions, e.g., Grimm et al. 2006, 2010), model verification and validation, and telling signal from noise in model structure and output (Grimm & Berger 2016). ABM challenges also entail making model design and analysis coherent and efficient instead of ad hoc, and identifying general principles underlying the systems' internal organization, steep learning curves for non-modeling experts (novices in particular), difficulty to scale ABM models or findings from one level to another, high sensitivity to detail (the other side of the problem is ABM's data hunger) as

well as stochastic elements, alternative decision models, and representation of spatial structure (e.g., An 2012; An et al. 2005; O'Sullivan et al. 2016; Parker et al. 2003). Equally important, ABMs are largely developed either on a PC (for exceptions see Tang et al. 2011; Tang & Bennett 2010a) or on an ad hoc basis with substantial variation in platforms, programming languages, model details and sophistication, and the modeler's preferences. These variations reduce ABM's capacity to facilitate high performance computing and handle big data (especially spatially and potentially temporally explicit data). According to the feedback we received from an NSF-sponsored conference (An et al. 2018), the following challenges are of particular attention.

1. Modeling human decisions, especially decisions regarding their interaction with the environment. There is increasing evidence that this topic is of prime interest. For instance, one review paper about modeling human decisions using ABMs (An 2012) has become highly cited in the past 7 years (547 citations as of December 28, 2019) according to Google Scholar. A more recent publication (Groeneveld et al. 2017) shows that most models of land use/land cover change use simple utility functions to represent decision making and that, while sometimes more sophisticated representations are used, in none of the 134 reviewed article alternative decision models were compared. However, such comparisons are needed to select and develop the most flexible and predictive decision models ("pattern-oriented theory development", Railsback & Grimm 2019; see also the framework for systematic comparison and development of human decision models suggested by Schlüter et al. 2017).
2. ABM transparency and reusability. These issues have been mentioned as one of the bottleneck problems for the ABM community (An et al. 2014; National Research Council 2014; Parker et al. 2003), even though important work suggests advances (e.g., the COMSES node at www.comses.net). Without adequate transparency and reusability, it is not only difficult to verify and validate ABMs, but also wastes a large amount of resources, such as modules and programming libraries that have been developed and tested by ABM experts. When ABMs are largely not reusable, non-transparent, and difficult to be validated, it is challenging, if not impossible, to compare ABMs from different sites or applications and to generalize commonalities out of locale-specific details. As a result, the usefulness of ABM in hypothesis testing and theory formulation is reduced (An et al. 2014; Rindfuss et al. 2008). Correspondingly, it is sometimes problematic to convince people what insights may come uniquely from ABMs instead of traditional equation-based models, such as various types of regression models. Currently, the ODD protocol (Grimm et al. 2006, 2010; Polhill 2010; Polhill et al. 2008)² is the most widely used standard format for describing ABMs, which is also designed to facilitate replication; it has already contributed to integrating research from different disciplines using ABMs (Vincenot 2018). Likewise, the benefits of starting a modelling project from the replication of existing models, rather than starting from scratch, are increasingly acknowledged (Thiele & Grimm 2015; Hauke et al. 2020).
3. Validation of ABM. This has been a problem besetting ABM modelers and users for many years (An et al. 2005; National Research Council 2014; Parker et al. 2003), and many doubts arise from this difficulty (Couclelis 2002; Roughgarden 2012). Without robust model validation, the reliability of ABM cannot be established, limiting its usefulness and application in various contexts. Pattern-oriented modelling has been suggested as a strategy that allows us to compare model output to multiple, instead of a single, patterns, observed at different scales and levels of organization. Each pattern is used to reject unrealistic process representations or parameter combinations (Grimm & Railsback 2005; Railsback & Grimm 2019). By this multi-criteria design and testing, the structural realism of ABMs is increased and trust in the model's validity is also increased.
4. ABM Software and Big data ABM. This emphatic topic comes from the increasing availability of big data, such as high resolution remote sensing imagery and large detailed, human socioeconomic datasets (Wang et al. 2013). Currently ABMs are largely based on relatively small or local scales, limiting the usefulness of ABM in large (spatial extent) and high-resolution contexts. A small set of exceptions, however, exists in parallel computing, (Tang & Bennett 2010b,a; Tang et al. 2011).
5. ABM theories. We need testable, generative theories to understand how complex systems patterns and dynamics may emerge. Intuitively, buffer and recovery mechanisms based on diversity, heterogeneity, and adaptation are key to sustained functioning of systems, but it is challenging to quantify and understand their interaction (Egli et al. 2019).

3.3 A key to the further advancement of the theory of agent-based complex systems is a systematic development of theories of human behavior. It is critical to distinguish between imposed behaviors, which are based on empirical and thus not transferable rules, and emergent behaviors, which emerge from first principles underlying each

agent's decision making in response to changing conditions. While in ecology such first principles, such as fitness seeking and energy budgets, are increasingly used, corresponding principles still need to be identified for human behavior. A promising avenue for future research in this field is acknowledging the context-dependency of human behavior. In panic reaction, humans can be represented as "Brownian agents", i.e. like physical particles, in other situations simple utility functions may be suitable, while in "hedonic modelling", emotions such as fear are the central concept (Eliassen et al. 2016). Only if we are getting better in capturing the emergence and context dependency of human behavior will we be able to better understand and predict the dynamics of agent-based complex systems and develop theories for these systems.

This Special Issue

- 4.1 The aforementioned challenges regarding ABM may lead to inadequate or inappropriate ABM uses, constraining the advancement of the science in question if not addressed with high priority in ABM research. This special issue features three standalone, yet interrelated goals: (1) defining complex systems as agent-based systems, the object of a new, much-needed generic systems theory; (2) summarizing the generic features of such systems and the key questions about them; and (3) providing case studies where these features are relevant and these questions are addressed using agent-based modeling.
- 4.2 Ligmann-Zielinska et al. (2020) offer a comprehensive overview of sensitivity analysis, providing a roadmap for ABM modelers or users to choose the most appropriate methods when performing sensitivity analysis. The methods for sensitivity analysis may vary, depending on whether the goal is to identify a proof of concept, to produce predictive outcomes (or to increase decision-making capacity), or to conduct exploratory modeling and gain insight into the effects of complexity features on a complex system of interest. Despite increasing use of ABM in many disciplines, broader adoption is hindered by a set of methodological and conceptual challenges. This context explains well the impetus of Manson et al. (2020) to explore methodological issues of spatial ABMs (SABM): space and time representation, scale and space, predictive or explanatory use of ABM, balance between model simplicity and complexity, qualitative modeling and collaboration, and the role of ABM in advancing theory or generative science. Manson et al. also provide a summary of common platforms that facilitate SABM development. On the other hand, An et al. (2020) provide an empirical study of employing ABM to integrate data and models from various domains (bearing different spatial and temporal scales by nature) in an agent-based complex system. With simulation of human and monkey activities, An et al. performed ABM-based experiments to examine the social and ecological impacts of a conservation policy, showing a surprising outcome that cannot be explained by common statistical or equation-based models. Another empirically calibrated ABM by Tang & Yang (2020) seeks to identify space-time locations of land developments at critical thresholds of water quality in eight North Carolina counties. In this model, land developers interact with land owners and decide where and how to develop land parcels, producing complex landscape patterns that drive spatiotemporal patterns of water quality over space. The work by Hauke et al. (2020) shows that replicated simulation models can be used to develop theory. In a context where most agent-based models have not been replicated, it is often difficult to identify sources of information or insights in ABMs (e.g., from ad hoc assumptions or parameters or from theoretical insights). Applying the ODD (Overview, Design concepts, and Details) protocol and DOE (design of experiments) principles, the authors were able to develop experiments and generalize some theoretical insights built in a previous ABM, showing a promising use of ABM in generative science. The model by Dou et al. (2020) represents a new type of ABM — a systems simulation tool that quantifies the causes and effects of local land-use changes on distant locations using hierarchical modelling structure and the telecoupling framework. The model shows that potential subsidies from Brazilian government to local soybean farmers could reshape land uses in China through international soybean markets.
- 4.3 This special issue addresses ABM problems and challenges at a time in which the use of ABMs is exploding. It assembles seven exceptional teams (including modelers, users, and domain experts) to disentangle the ABM challenges and advance the ABM science. This special issue also aims to identify a set of impending tasks in several topical subareas, such as model testing and validation through sensitivity analysis (Ligmann-Zielinska et al. 2020) or replicability test (Hauke et al. 2020), ABM-enabled theory development (Manson et al. 2020; Hauke et al. 2020), modeling human decisions (An et al. 2020; Dou et al. 2020; Tang & Yang 2020), and ABM transparency and reusability (Hauke et al. 2020). We hope this endeavor will help prioritize specific resources and activities in relation to ABM advances, leading to coordinated, joint efforts and initiatives to advance the science and technology behind ABM. It is our sincere hope that all papers in this special issue help outline a clearer picture of ABM, including strengths, weaknesses, available resources, and future directions. The ABM science will advance more steadily when more users, developers, and commercial companies are engaged, allocating more resources to the science, technology, and application of ABM, enhancing ABM software and capabilities.

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Notes

¹We use the acronym ABM for agent-based modeling and ABMs for agent-based models throughout this editorial article. The term multi-agent systems (MAS) is also used to refer to agent-based models (Parker et al. 2003), but often rather refers to software agents explored in Artificial Intelligence research.

²A new version of ODD, which comes with extensive guidance for how to write an ODD model description and how to use it in different contexts, is under review (Grimm et al. 2020). The only change to the protocol itself is that the first element “1 Purpose” is now “1 Purpose and patterns”. This implies that the patterns are supposed to be listed now, which will be used to claim that the model is realistic enough for its purpose. Of course, the type and number of patterns used depends strongly on the model’s purpose (Edmonds et al. 2019).

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