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Rethinking the role of Agent-Based Modeling in archaeology

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ABSTRACT

Agent-Based Modeling (ABM) represents a methodology with significant potential for altering archaeological analytical practice. The continued growth in the number of publications that use ABM provides evidence for the significance of this emerging approach. However, the scope of the research topics investigated has not increased accordingly. A consensus exists among ABM practitioners, that once generally accepted by the field, ABM can make revolutionary advances within the overall archaeological research paradigm. Unresolved concerns within the archaeological community center on whether ABMs are sufficiently grounded in empirical data, are aligned with theoretical trajectories, and on the difficult task of mastering the computational systems. It is worth exploring these aspects of the disjuncture between the mainstream and ABM practitioners for two reasons – to frame a discussion of qualities of ABM that make it transformative and to provide guidelines for broadening ABM's applicability. With capacity-building in mind, offered here is a practical reference for the non-practitioner archaeologist considering ABM. A glossary is included of key terms used in the text to describe ABM methods and theory.

1. Introduction

Adoption of a major new methodology by a particular field of study is transformative when it allows the development of new possibilities previously unrealizable. For instance, the implementation of radiocarbon dating from the field of chemistry completely revolutionized the ways archaeologists organize time. More recently, the adoption of user-friendly Geographic Information System (GIS) software developed initially to map modern land use, made it possible to render and analyze multiple data sets and reshape the ways archaeologists conceptualize space. Both radiocarbon dating and GIS are now standard in archaeology.

Observing recent trends toward increased use of Agent-Based Modeling (ABM) in archaeology suggests the beginnings of at least a technological transformation, with the potential for substantial changes in methodology and theoretical frameworks. The annual rate of publications using ABM has increased substantially, especially after 2007, as shown in Fig. 1, based on a review by the authors of publications since 2000. Similar trends have already been noted in other social sciences for the use of ABM, pointing to the emergence of transdisciplinary approaches (Bankes, 2002; Moran et al., 2014). This article explores the reasons for expanded use of ABM, reflects on the challenges inherent in the method, reviews some of the ways ABMs have been used, and provides a practical summary of the modeling process for those not versed in the intricacies of computational approaches.

The sociology of science provides useful examples of how transformations occur in different fields of study. At least since the work of Thomas Kuhn (1962) the patterns that produce major shifts are well-known. Generally, transformations occur as a result of one or more conditions that promote advances: (1) integration of multiple paradigms across disciplines, as in interdisciplinary and transdisciplinary approaches (Cioffi-Revilla, 2014); (2) emergent challenges that galvanize the research community, such as landing humans on the Moon or the current push to understand climate change; (3) development of new technologies, such as larger telescopes or more powerful computers; and (4) research opportunity, as in the social and organizational contexts that may encourage new ideas (Hackett, 2011). Of these four change conditions ABMs most clearly represent a new technology, however, ABMs also offer a methodology to unify long-held discipline-based theoretical disjunctures (Gavin, 2014; Kohler, 2000) and open the path to fundamental challenges to epistemological assumptions (Hayles, 1991; McGlade and Garnsey, 2006).

Even with these potentials, ABM and computer simulation, which have been known in the field for about as long as GIS, have a checkered history of impact (see Lake, 2014, 2015 for a more complete review of the history of computer simulation and archaeology). At the same time that archaeology has witnessed an uptick

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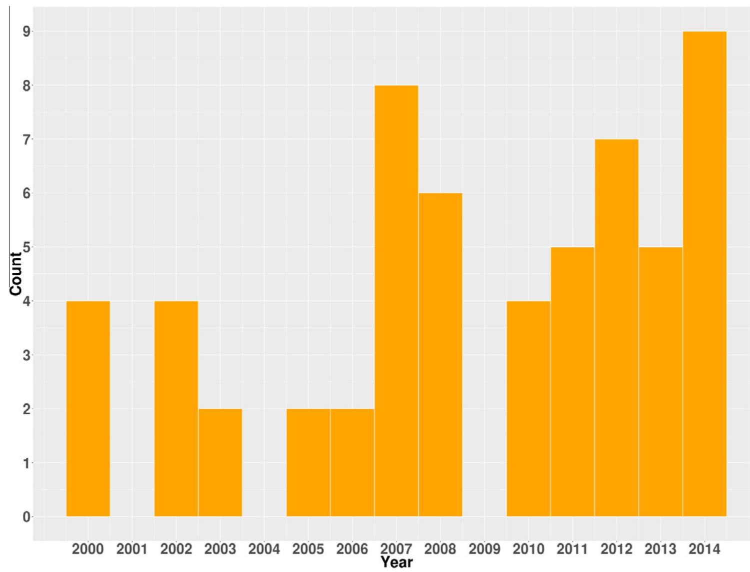

Fig. 1. A review of the use of ABMs in archaeology shows a rapid growth in the number of publications since 2000.

in numbers of ABM applications, the scope of research topics covered has not followed suit necessarily. In addition, its increase is still limited to a small, but slowly growing community of archaeologists targeting a select list of archaeological research interests. As Lake (2014:278) states in a recent review of trends in archaeological simulation, "The skeptic may point out, however, that simulation has only become unremarkable in certain fields of archaeological enquiry, in particular evolutionary archaeology and the study of human evolution, and cannot therefore yet be considered a 'mainstream' tool in the way that, say, geographical information systems are used...." It is worth asking why this is so, since as already illustrated, there should be little reason to doubt the ability of new methods adopted from other disciplines to fundamentally transform our investigations.

In brief, the mixed reception of ABM in the discipline of archaeology may be attributed to three factors: (1) ABM methods are viewed as complex and difficult to use; (2) ABM's theoretical foundations and computing capabilities until recently were not sufficiently developed to address what archaeologists needed and wanted; and (3) trends in archaeological thought had drifted away from quantitative approaches and questioned the ability of computer simulations to capture human complexity. These three factors were arguably legitimate criticisms in the 1970s through the 1990s and it is possible that the frustrations produced still linger when considering ABM as a potential method. Early criticisms of computational simulation also may have led to the absence of computational methods in many university archaeology programs. Additionally, the general lack, or even in some cases rejection of formalism in archaeological models written as if-then statements, has not enabled smooth synchronization between the two. By formalism, we mean the precise listing of logical statements about variables, assumptions about their behavior, and the consequences of these assumptions. We do not argue that ABM is appropriate for studying every aspect of the human condition, but do argue that its potential to make advances especially within post-modernist, anthropological perspectives has been limited by the "computation = reductionism" argument. It may be correct to say that ABMs are reductionist in that they focus on only a few characteristics of a human system, but ABMs are models and just like any other explanatory paradigm, the researcher cannot study all characteristics at once. Therefore, ABMs are no more reductionist than more commonly used explanations in archaeology.

Yet, among practitioners of ABM, there is a clear consensus that ABM, once generally accepted by the field, will make revolutionary advances within the overall archaeological research paradigm (Barton, 2014; Crabtree and Kohler, 2012; Madella et al., 2014; van der Leeuw, 2004). It is worth exploring this disjuncture between the perspectives of the mainstream and ABM practitioners for two important reasons: to serve as a framework to discuss the precise qualities of ABM that make it transformative and to provide guidelines for the changes necessary to broaden ABM's applicability to archaeological mainstream interests.

2. Opening the black box

ABMs are a class of computational models that simulate the behavior and actions of agents (whether individuals, families, villages, or other units of interest) as an integral aspect of interpreting the whole system (Lake, 2015). Railsback and Grimm (2012) have prepared an excellent guide to ABMs and the popular simulation package NetLogo. ABMs were developed in order to vitiate problems encountered by researchers when applying formal mathematical models to complex phenomena (Railsback and Grimm, 2012). Complex phenomena should not be confused with other uses of the word complex or complexity in archaeology (Kohler, 2012). Complex phenomena result from a series of interdependent processes and relationships that cannot be understood by analysis of the individual parts that make up the whole, or even in terms of one empirical instance (Hayek, 1980; also see Glossary). A readily understood example of this is the palimpsest archaeological record. As archaeologists, we readily recognize that palimpsests depend on more than one circumstance, each with its own working details—natural formation process, direct human action, taphonomy, reuse and recycling, and even historical dependency (Bailey, 2007; Holdaway and Wandsnider, 2008). By isolating one of these processes for further analysis, we come to understand it better but never in light of how it is actually related to all of the other circumstances responsible for the palimpsest we see. Or using a non-archaeological example, is it desirable, or even possible to define a basketball team's strategy by analyzing one play of the game?

A long-term criticism of ABMs is that they are too opaque; they are "black boxes" where no one except the programmer can evaluate what goes in and what comes out (Topping et al., 2010; Wobst, 2010). In other words, while the basic concept is intuitively clear to most, that a system is more than just the sum of its parts, the actual methodology behind implementing the behavior of individuals and what this tells us is not clear. The black box problem has been recognized by the ABM community and a number of solutions have been proposed in the literature to aid in standardizing descriptions of models and publishing code. In archaeology, the Overview, Design Concepts, and Details (ODD) protocol has been the most commonly adopted standard for model description. According to the authors of the protocol, one of the primary objectives of the ODD is to make model description more understandable and complete, to the point that a model would be reproducible by anyone just from reading the ODD (Grimm et al., 2006, 2010). The ODD framework is divided into seven sections: "purpose, state variables and scales, process overview and scheduling, design concepts, initialization, input, and submodels." (Grimm et al., 2006:115). Recently, there has been a push to develop open source repositories where models, code, and associated documentation like the ODD are published and made accessible to other researchers. (See CoMSES Net Computational Model Library <http://www.open-abm.org> for one such repository that includes a number of archaeological examples as well as Rollins et al., 2014.)

Reproducibility is a key concept in ABM and is fundamental to the scientific method, but is not something frequently addressed when doing standard archaeological work. Excavation of a site does not allow replication by independent researchers. If an experiment is reproducible this increases certainty that the results are not idiosyncratic, a result of latent assumptions, or even an artifact of the model code, but are actually a result of the experimental processes. The ODD is a standard that creates transparency for evaluation by other researchers as well as the opportunity to examine our archaeological assumptions (Popper and Pichler, 2015). Reproducibility can be difficult to approach in archaeology; ABMs with proper documentation provide archaeologists with a tool for evaluating the strength and reproducibility of their inferential narratives.

Another way to conceptualize an ABM, that is not commonly used in archaeology, is through Unified Modeling Language (UML). A UML is a set of standardized diagrams resembling a flow chart that graphically represents agents, behaviors, environments, and their interactions and relationships through time (Bersini, 2012). See Cioffi-Revilla et al. (2010) for an example of UML as implemented for an archaeological ABM. Other alternatives exist for documentation, but the point here is that the code and description of an ABM should be published either with the body of the main manuscript or in an accessible repository referred to in the manuscript. Even more importantly, the description should be understandable to a broad archaeological audience.

The recent volume edited by Wurzer et al. (2015) provides several example articles that implement ABM's latest advances as applied to an archaeological context. The reader is referred to a large group of recent publications that incorporate a variety of approaches to complex phenomena in archaeology (Balbo et al., 2014; Barton, 2014; Barton et al., 2010, 2011, 2012; Barton and Riel-Salvatore, 2014; Breitenecker et al., 2015; Crema, 2014; Crema et al., 2014a; Gavrilets et al., 2010; Godino et al., 2014; Heckbert, 2013; Kohler et al., 2012a,b; Kohler and Varien, 2012; Ortega et al., 2014; Premo, 2012; Rogers, 2013; Rogers et al., 2012; Rouse and Weeks, 2011; Rubio Campillo et al., 2012; Turchin et al., 2013; White, 2013). The discussion in these articles, however, often concentrates on a particular case study or research question. Here, we wish to focus on epistemology and implementation of ABMs in an archaeological context. With a familiar example from archaeology, political organization of chiefdoms, the following illustrates the process of creating an ABM from conceptualization to final analysis. As a result of processual and post-processual critiques of archaeological epistemology, the study of political organization has moved from preoccupation with trait lists to concerns with dynamics (Beck, 2003; Cobb, 2003; Earle, 1993; Pauketat, 2007). The concept of power has been of particular interest, especially how power is obtained and maintained along with the role of individual agency (Cobb, 2003; Crumley, 1995). Agency as defined by Dobres and Robb (2000:8) is the "way in which societies' structures inhabit and empower agents, those agents' aims, ideals and desires and the material conditions of social life." In reference to this definition, a study of the role of power in political organization would use the material record to comment upon three domains—the agent or individual, the socio-structural context, and the interaction (specifically the formation of power) between the two.

ABM allows the researcher to explicitly formalize and operationalize all three domains. In the example under discussion, the goal is to understand power negotiation in past societies through actions of individuals focusing on one particular style of sociopolitical organization—the socio-political hierarchy. This is found in a variety of forms and levels of differentiation, but referenced here is the style of political control found in what archaeologists refer to as chiefdoms. Fig. 2 is a graphical interface of an example model published in the open source ABM repository *CoMSES Net Computational Model Library* (Cegielski, 2010). This model can serve as an abstract laboratory for theory building about commonly held assumptions about chiefdom behavior. Exploring the developmental concepts of this model serves to open the "black box" of ABM, illustrates how conceptualization of agent behavior is implemented in a "social" model, and how this conceptualization makes ABM different.

In Fig. 2, the circles represent agents. An agent is a collection of behavioral rules and attributes that represent its identity. The lines connecting circles represent relationships between two agents. The larger collectivities of circles represent organization at the chiefdom level. When collectivities connect, they increase the level of organizational complexity (in this example, forming a paramount chiefdom).

Whether explicitly acknowledged or not, behavioral rules applied to agents in the model are theory-driven. In the above example, behavioral rules of individuals are based on research in other fields demonstrating that hierarchies commonly arise through a process called *preferential attachment*. This, in essence, is the tendency of individuals to connect with more popular members of the hierarchy, or those who have other qualities that foster attachments (Barabási and Albert, 1999). This type of process is recognized by archaeologists who discuss, for example, the build-up of political power through mobilization of labor and surplus (Earle, 1993; Hayden, 2001; Stein, 1998). An aggrandizing individual begins to collect surplus in the form of power over more and more individuals, in a self-reinforcing cycle. This is only one of many competing theories that might explain the beginnings of a political hierarchy, but it is one that can be formalized and tested and one in which factors promoting or constraining self-reinforcement are not well understood.

In this example, we use a common theory that can be formalized through behavioral rules within an ABM. In computer programming, behavioral rules are coded through a series of conditional statements, (e.g. if/then; if/else; do/while) and probabilities. The rules hidden inside the black box of this model governing individual behavior adhere to the following general pattern:

<u>Model set-up</u> (the hierarchy does not exist at this point): <*Two individuals are created with a chance of connection*>

<u>If/then statement</u>: <*If an individual has no connections, then a connection is sought*>

<u>Probability</u> (this connection is based on the attraction of power): <*The probability of connecting to another individual is biased toward the most powerful individuals*>

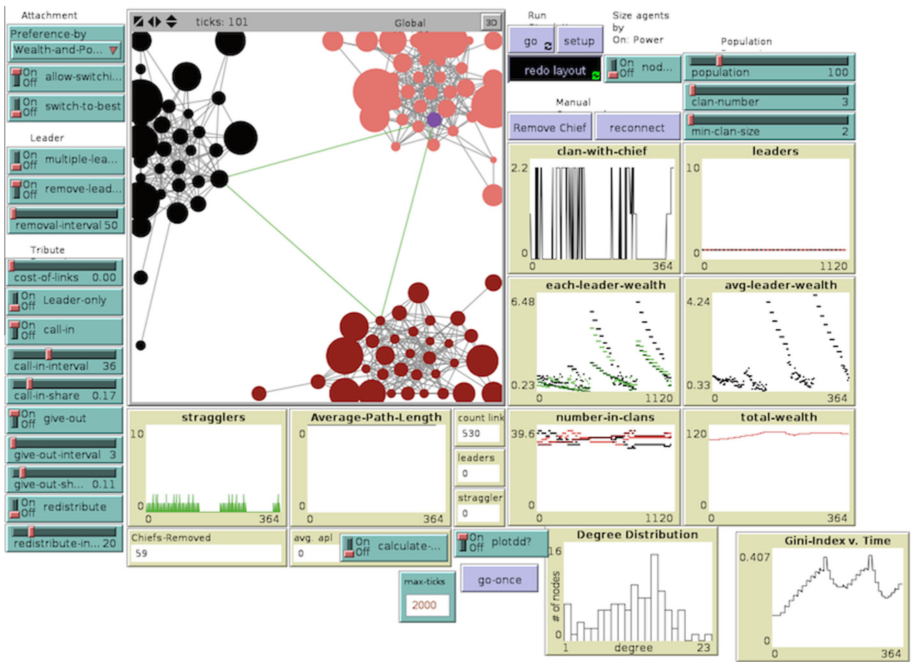

Fig. 2. Model graphical interface. Graphical interface of Chiefdom ABM created in NetLogo software platform. (Cegielski, 2010 "Chiefdoms and Structural Resilience to Stress," with code and documentation can be found at https://www.openabm.or g/search?content=chiefdoms). Colors represent simple chiefdoms connected (green lines) through their chiefs to form a complex chiefdom, governed by the most powerful individual, the paramount chief (in purple).

At this point, the process repeats when another agent is created. The emergence of the hierarchy results from the buildup of bias over time as each new connection is introduced. The emergence of the hierarchy is an important aspect of the model since it was not part of the initial programming. An emergent property is important evidence that the model is behaving in accordance with the hypothesized characteristics of the sociopolitical system under study. Once the hierarchical structure is created the model can be used to generate archaeological expectations for a variety of research questions. Some examples include: (1) What sociostructural differences coincide with increasing levels of population?; (2) How is the duration of highly complex chiefdoms changed when competition (the addition of more, second-order chiefdoms and/or leaders) is increased?; (3) When do chiefdoms transition from chiefdoms to states (and just as importantly, when and why does this change *not* occur)?; and (4) How does the agency of a single individual (i.e., the death of the leader or a leader's decision to increase surplus mobilization) influence the structure of the chiefdom? ABMs can be built to guide data collection, to operationalize the middle-range, and to evaluate the plausibility of a variety of bridging expectations between theory and the material record (Epstein, 2006).

Understanding the role of probability in simulation models is crucial to opening the "black box" of ABM and to illustrating its congruity with special problems facing archaeologists. We are limiting specifically the discussion of probabilities to uncertainty about process or behavior and their effects on the realization of outcomes, i.e. not every person experiences the same processes the same way. This is different than uncertainty in which the specific quantities of a variable may be unknown (Briggs et al., 2012). Probabilities are often used when a behavior is difficult to quantify a priori (Ligmann-Zielinska et al., 2014). It was stated earlier that a study of the role of power in political organization would use the material record to comment upon three domains—the agent or individual, the socio-structural context, and the interaction (specifically the formation of power) between the two. Archaeologists are well aware that this is a complex process involving the justification and use of multiple valences of material proxies for social phenomena having their own complex causalities. In addition, archaeologists recognize that experimenting with the real system of interest, the complete material record of the past, is impossible since the producers of this record are not directly available nor are many of their material remains. One common option for dealing with these challenges is to calculate a single value that serves as best estimate of outcome for each course of action (Briggs et al., 2012; Troost and Berger, 2012). This process is called *point estimation*. The serious problem with this approach is that most archaeological processes are not observable, making them exceedingly difficult to disaggregate.

Alternatively, we can accept the reality of uncertainty inherent in complex human systems and use it to create more realistic models. In the above example, a probability of connection is used because of the conviction that it is unrealistic to assume that all individuals will connect in lock-step to the most powerful individual available. When studying human systems, we can increase the realism and explanatory power of our models by exploring a probability space of variability in human behavior within a certain context of social, cultural, or environmental constraints.

3. Meeting the challenges of archaeology: An evaluation of Agent-Based Models

The discussion above was meant to remove some layers of opacity concerning the use of ABMs in an archaeological context, a perception we propose has led to its mixed reception. We additionally have argued ABM and computer simulation initially did not meet the needs of archaeology and therefore did not follow the same "mainstreaming" trajectories of GIS and radiocarbon dating. The value of a tool to a field is in the needs that it serves and whether the challenges faced by that field make it necessary (Bankes, 2002).

A recently published synthesis produced the following mission statement about the challenges most important to archaeologists (Kintigh et al., 2014:879):

These challenges focus on understanding the dynamics of cultural processes and the operation of coupled human and natural systems, recognizing that humans—mediated by culture—both affect and are affected by their natural environments. The challenges addressed questions of emergence, complexity, demography, mobility, identity, resilience, and human-environment interactions. There is a notable lack of concern with the earliest, the largest, and otherwise unique.

We are not able to discuss each of the themes in this article (see Cobb, 2014 for additional perspectives). We do, however, suggest the need for self-reflection about our current methodologies and about whether they serve the practical requirements necessary to meet the above mission statement. And while we cannot assess every method commonly used in archaeology in terms of these challenges, we can assess current usage of ABM.

4. Current thematic trajectories

Not unlike what has proven to be the case for the use of GIS in archaeology, ABM is widely applicable to a broad range of archaeological topics. This is supported by the fact that the scope of archaeological challenges addressed by ABMs has widened in step with the increasing amount of publications. From our survey of 52 publications in archaeology that use ABM as their primary methodology, we have identified six themes. There are a number of other ways that we could have grouped these publications (see Lake, 2010 and Mithen, 1994 for alternatives). Given the breadth of topics, a study may incorporate multiple topics, however, the objective is to highlight the scope of ABM's integration with commonly used archaeological themes. Listed in order from most to least common by the number of publications, they are: (1) Historical; (2) Social Complexity; (3) Formation processes; (4) Human Ecology; (5) Evolutionary processes; and (6) Complexity Science. While we cite many of the relevant studies, the pace of publication and diversity of outlets makes it impossible to be totally inclusive. Our sample does not include conference presentations, publications before 2000, or publications that are not primarily archaeological in their intent. Additionally, we have not included publications from 2015 in this tally because the year is not over at the time of this writing. Our impression, however, is that the pace of publication is increasing even further (e.g. Bogle and Cioffi-Revilla, in press; Cecconi et al., 2015; Cioffi-Revilla et al., 2015; Rogers et al., 2015). The following is a discussion of each of the major themes.

4.1. Historical

This emphasis focuses on the history of interactions between humans and their environment. The aim is to use ABM to simulate a series of "what if" scenarios constrained by archaeological data to reconstruct a detailed environmental and social history that best fits an archaeological or time-series dataset (Kohler et al., 2000; Axtell et al., 2002; Christiansen and Altaweel, 2005, 2006; Dean et al., 2000; Gumerman et al., 2003; Heckbert, 2013; Johnson et al., 2005; Kohler et al., 2007, 2012a; Murphy, 2012; Varien et al., 2007; Wilkinson et al., 2007a,b; Wu et al., 2011). The what-if scenarios are explored by defining as parameters the characteristics of the agents and the environment. A well-known example of this type of modeling is the Artificial Anasazi ABM (Axtell et al., 2002), which simulates the population dynamics between A.D. 800 and 1350 in the Long House Valley in Arizona. The aim of the model is to investigate the factors that affect population levels for the Long House Valley by instantiating a number of parameters including social units and paleoenvironmental variables derived from empirical data. Some uncertainty exists about the range for each parameter that best fits the archaeological record, so these parameters are optimized during modeling by searching an "eight-dimensional parameter space" in order to find the most efficient combination of parameters. The authors conclude that "the output from the current model closely reproduces the record of the archaeological survey" (Axtell et al., 2002:7278). Results from the study shown in Fig. 3, represent in red the close match between the simulated settlement patterns on the left and the historical settlement patterns on the right.

The success of the model is assessed by the consistency of its optimized results with the archaeological record in that particular time and place (Janssen, 2009). The ability to model agent heterogeneity, which is difficult to model with formal mathematical methods, is an advantage over other approaches. We also note that the inability to conduct reproducible experiments is a major impediment in archaeology, while computational modeling offers this potential. Historical ABMs such as the Artificial Anasazi model have a wider resonance in archaeology than other types and are frequently cited.

Approximately 30% of the ABM models surveyed for this article, published between 2000 and 2014, are epistemologically framed in the manner of the Artificial Anasazi ABM. By this, we mean they are framed instantiations of a particular slice of the empirical, archaeological record. This is hardly a surprising finding, since a primary aim of archaeology and what makes it unique, is its ability to explain patterns in the material record. The authors of Artificial Anasazi never intended to arrive at generalizations beyond the history of the Anasazi; they state that they are successful in explaining *this* history (Axtell et al., 2002). This use of ABM has merit, especially for archaeologists interested in understanding historical and specific contexts as explanation. The results can then be extrapolated for wider application.

4.2. Social complexity

The studies in this group focus on the processes that account for the formation of polities typically described as chiefdoms or early states. One of the long-term challenges for archaeology is interpretation of the rise of social complexity and the subsequent spread of such polities that incorporated political control hierarchies, in conjunction with collective action as specialized social, technological, and organizational functions. Closely associated with these interpretations is the emergence of cities, population growth, and organized warfare. Some of the studies in this group also incorporate basic principles of complexity science, as discussed in a following section. Again, approximately 30% of the surveyed models are applied to research problems associated with social complexity (Alden Smith and Choi, 2007; Altaweel, 2014; Cioffi-Revilla et al., 2007, 2010; del Castillo et al., 2014; Doran, 2000; Gavrilets et al., 2010; Griffin, 2011; Griffin and Stanish, 2007; Kohler et al., 2012b; Read, 2002; Reynolds and Lazar, 2002; Reynolds et al., 2002; Rogers, 2013; Rouse and Weeks, 2011).

Over the decades explanatory theories and descriptive interpretations have not only resulted in a few areas of consensus, but also in a forest of divergent perspectives (e.g. Algaze, 2001; Chapman, 2007; Ferguson and Mansbach, 1996; Roscoe, 1993). While we have learned much about how complex systems emerge, sustain themselves, and often collapse, some of the most telling findings are about what complex societies are not. All human societies are in some sense complex, which in itself provides a powerful motivation for the use of ABMs. Further motivation emerges from findings that confirm pathways to complexity are not linear and cannot be explained by demographic or environmental determinism (Feinman, 2013, 1995:274). Some of the studies in this group provide interpretations of the motivations behind the use of ABMs, while others focus on various theoretical issues (e.g. Cioffi-Revilla

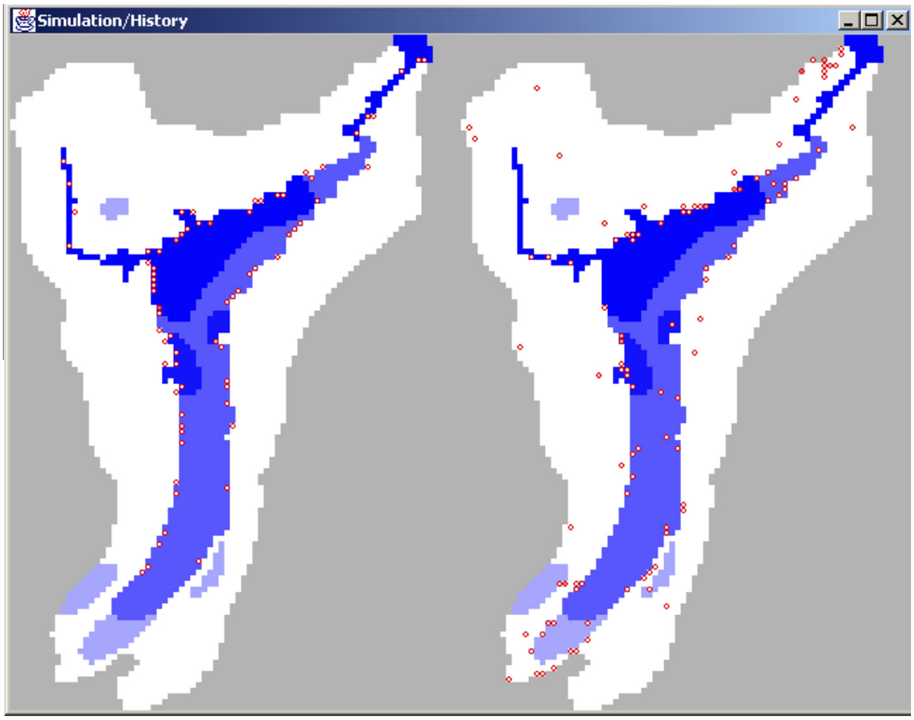

Fig. 3. Example of a Historical ABM. Simulated and historical settlement patterns, as red points, for Long House Valley, AZ in A.D. 1125 (from Axtell et al., 2002, copyright [2002] National Academy of Sciences, U.S.A.). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

et al., 2010; Cioffi-Revilla, 2014; Doran, 2000). Studies of social complexity have focused on both the processes that produce increasingly complex systems (e.g. Barceló et al., 2015; Read, 2002; White, 2013) and on the interactions that occur between already formed polities (e.g. Bogle and Cioffi-Revilla, in press; Gavrilets et al., 2010; Griffin, 2011; Griffin and Stanish, 2007; Kohler et al., 2012b; Rogers, 2013; Cioffi-Revilla et al., 2015; Rouse and Weeks, 2011).

The models developed in this group range from simple abstractions to very complex "total worlds" designed to replicate many aspects of a social group in a particular place. An example of a recent study focused on basic organizational principles is that by Barceló et al. (2015). Their work utilizes a geographically specific social context for hunter–gatherers. Situated in the prehistory of Patagonia, the study explores the interactions inherent in the emergence of ethnicity and territoriality. At near the opposite end of the social complexity spectrum is a study by Cioffi-Revilla et al. (2015) based on polity formation in the Early Iron Age of Inner Asia. This study explores the dynamics of polity formation, involving control hierarchies, social power, forms of conflict, and polity disintegration. Fig. 4 illustrates an example of the scale and time duration for a sub-sample of simulated polities. The time-series graph displays the entrance into, fluctuation during, and exit from the simulation in terms of the power of each polity as shown by a uniquely colored line. Power in this simulation is "a multiplicative indicator of military capability and territorial size" (Cioffi-Revilla et al., 2015). The patterns result from rebellions, conquests, and secessions among polity members. These results are similar to those from empirical comparative studies of the rise and fall of early empires (Taagepera, 1979). Although the studies in this group are generally situated in a particular region, the research objectives are fundamentally oriented toward interpreting the nature of collective action at different scales.

4.3. Formation processes

Nine of the articles in our survey implemented ABMs as artificial laboratories to test assumptions about the formation of the archaeological record (Brantingham, 2003; Brantingham et al., 2007; Barton and Riel-Salvatore, 2014; Crema et al., 2014a,b; Lenoble et al., 2008; Premo, 2006, 2014; Reynolds et al., 2008; Rubio Campillo et al., 2012). These are conducted to test the reliability of material proxy measures for various behaviors. Possibly the first study conducted in this category is Brantingham's (2003) model of stone raw material procurement. Brantingham introduces the idea of the "neutral" model as a possible explanation for the variation seen in the archaeological record in the representation of stone raw materials. The neutral model consists of an ABM made up of individual foragers in a landscape operating under completely neutral assumptions, in that they walk randomly, procure resources in a uniform environment, and then discard consumed resources. This model demonstrated that it could reproduce patterns in raw material richness qualitatively similar to those commonly observed in the archaeological record. The record could be produced independent of archaeological assumptions that optimal foraging strategies must influence stone raw material procurement patterns. Null hypothesis testing of this type may not be novel to archaeology, but the ability to test a neutral model by actual implementation of the temporally, dependent processes of archaeological site formation and the creation of a virtual archaeological palimpsest that can be compared empirically is innovative. The use of ABMs for virtual site formation is clearly a powerful tool but its potential is still underutilized. Archaeological theories are tuned to and developed in ethnographic time scales that cannot deal effectively with the palimpsest/time-averaged character of the archaeological record without interposing a simulation (Kohler, personal communication, May 22, 2015). Other recent examples of innovative uses of this approach include a

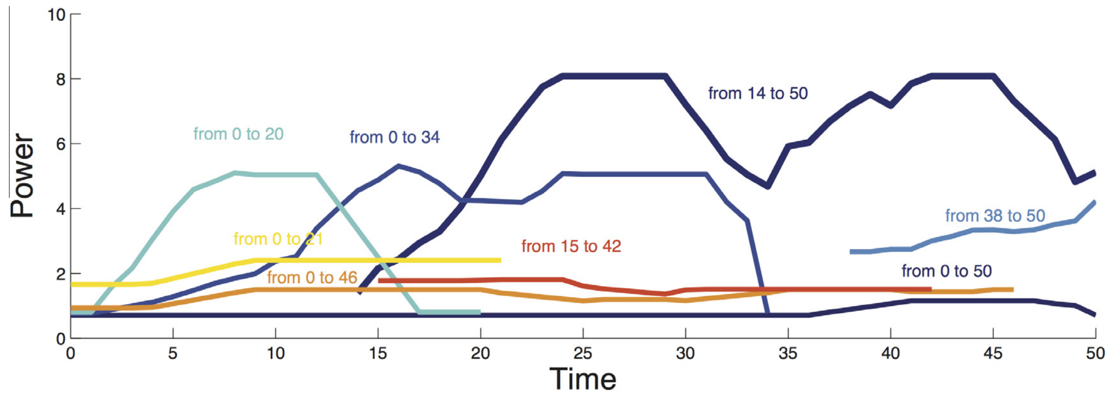

Fig. 4. Example of model output from the Hierarchies model showing the relative power and duration of a series of simulated polities (from Cioffi-Revilla et al., 2015).

study by Barton and Riel-Salvatore (2014) on the formation of lithic assemblages and a major study by Watts (2013) that modeled alternative, virtual records of exchange under a variety of assumptions to understand the evolution of the Hohokam economy in the US Southwest.

Another example of this style of approach is Crema et al.'s (2014b) "methodological simulation" constructed to evaluate the biological evolutionary concepts of branching (population fissioning), blending (i.e. trade and exchange), and the evolution of similarities in patterns of spatial variation in culture. They generate a series of artificial archaeological records with parameterized evolutionary processes and then evaluate whether the signals of these processes are truly distinguishable from each other in the archaeological record. The model design is contextualized in a grid space with each cell containing a maximum of one settlement of agents. Each agent is associated with a single cultural trait. The model is initialized and the distributions of settlements, agents, and traits updated according to the evolutionary process to be emphasized. This type of approach is an example of how ABM can be used simultaneously as a theoretical (in this case, evolutionary theory) and methodological testing ground to evaluate the effectiveness of middle-range assumptions, in terms of their abilities to distinguish patterns that are actually reflective of the cultural process of interest.

4.4. Human Ecology

Human Ecology studies the relationship between humans and their environments. Approximately 15% of the ABM models surveyed take an approach explicitly in line with concepts from this theoretical paradigm. This includes a number of more recent models designed to understand coupled natural-human systems. The long-term, strong relationship between archaeologists interested in human/environment dynamics and ABMs derives from ABM's developed capacity to understand principles of adaptation and feedbacks, both germane to archaeology's emphasis on understanding the influential role of the environment in human behavior.

In general, Human Ecology models focus their attention toward developing and testing simulations of interactions between land-use and landscape evolution (Altaweel and Watanabe, 2012; Balbo et al., 2014; Barton et al., 2010, 2011, 2012; Crema, 2014; Lake, 2000). They are often, but not always, explicitly spatially located in that a realistic paleolandscape is used as the context for agent and agent–environment interaction. The agents operate according to a set of behavioral rules and these actions feed back into the environment. The concept of environment is normally used broadly to include natural, social, and built environments, but in the application of ABM to archaeology, environment generally refers to the natural environment. A primary example of this type of research is a long-term initiative called The Mediterranean Landscape Dynamics (MedLands) project, which is producing a computational modeling laboratory for studying the recursive interactions of agropastoral land-use and landscape evolution (Barton et al., 2012). The project is designed around intensive study areas in eastern Spain and western Jordan and models a paleolandscape in a raster-GIS environment based on biophysical processes, climate, and vegetation models. By intensive, the authors mean the scale modeled is specific to a particular valley with empirical geographic coordinates and topographic features. The ABM of agropastoralists is then rendered in this environment. This project has a number of analytical goals and is capable of a wide range of experiments from the effects of variation in land-use practice to the ecological consequences of socially moderated site placement. The experimental results of socially moderated site placement are reproduced in Fig. 5, where each small dot represents a different topographic settlement choice of locality and each color[1] a vegetative community resulting from this social choice. Beyond archaeological investigations, the project's results also can be used to systematically quantify the role humans have had in shaping the modern environment. While Human Ecology models are often geographically explicit, they are not meant to reconstruct any one past society as the Historical models are. The power of these models lies in their ability to improve our understanding of long-term human–environmental change caused by *processes that can no longer be observed*, "using the archaeological record as a means of testing and refining models of the complex interactions between societies and the natural environment, rather than a basis for inference" (Barton et al., 2012:50–51).

4.5. Evolutionary processes

In the most general sense, models of this variety use Darwinian evolutionary principles to explain the processes behind particular patterns in the archaeological record. Models of this type, unlike the two prior examples, are abstract in that they seek to elucidate the general evolutionary processes that explain changes in material culture through time and are not necessarily interested in specific spatial or historical contexts. Evolutionary ABMs make up approximately 10% of the models in our survey (Conolly et al., 2008; Mesoudi and O'Brien, 2008a,b; Perreault and Brantingham, 2011; Premo and Kuhn, 2010; Reynolds, 2008).

Perreault and Brantingham's (2011) article addressing forager mobility serves as demonstration of how ABM has been used to explore cultural transmission, or the process of passing on social

[1] For interpretation of color in Fig. 4, the reader is referred to the web version of this article.

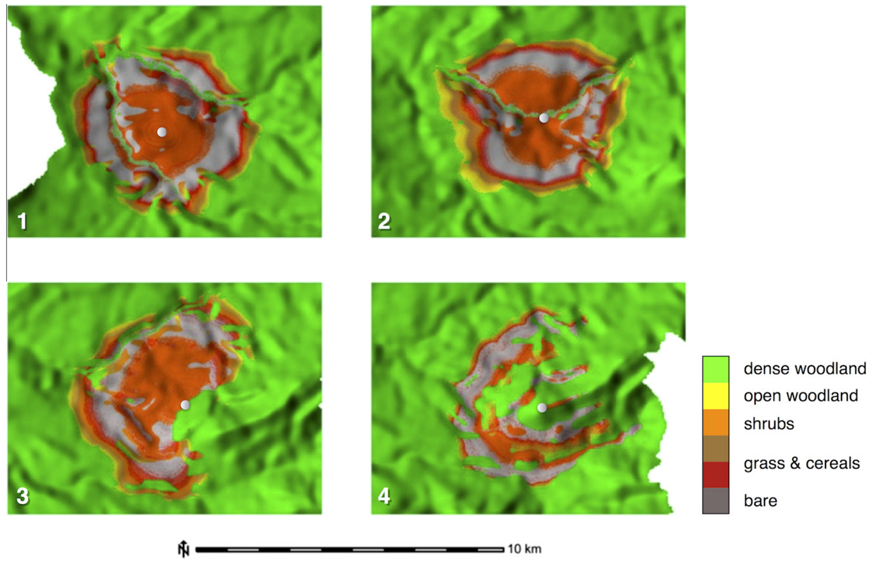

Fig. 5. Example of a Human Ecology ABM, where the settlement-choice (represented by the gray dot), interacts with the evolution of the local ecology of a small region in Eastern Spain, modeled as a dynamic, PaleoDEM. Four different settlement choices were modeled (from Barton et al., 2012).

information through inheritance in a similar sense to biological inheritance. Their strategy is "to extend Binford's work on the archaeological implications of the forager–collector model to investigate how different mobility regimes impact cultural transmission" (Perreault and Brantingham, 2011:64). They model two foraging groups who operate from home bases in an artificial, spatially continuous environment. One of the groups starts with a novel trait and when the groups contact each other the trait can be passed. The number of time steps it takes for cultural transmission to occur is counted. They conclude that the number of moves a forager makes before returning to home base has a non-linear impact on the time it takes for transmission to occur. In their model, foraging and collecting falls along a continuum. Collectors make less moves; Foragers make more moves. Among a set of several interesting results from their experiment, the authors are able to determine that mobility-driven cultural transmission is equivalent to a Poisson process, and that random imitation cannot be discarded as a process in spatially structured populations. Thus, a typically non-spatially explicit concept – cultural transmission – is reconsidered archaeologically and spatially using ABM.

4.6. Complexity Science

Several archaeological ABM models refer to Complex Systems Theory and concepts associated with Complexity Science as their main conceptual frameworks (Barton, 2014; Griffin, 2011; Rogers et al., 2012; White, 2013). The basic aspects of complexity science include the idea of a hierarchy of organized functions, emergent patterns across scales, self-organization over time, nonlinear interactions, open system boundaries, and holism, in which the whole is greater than the sum of the parts (Holland, 1998; Kay et al., 1999; Robinson, 2009). The limited number of these models may reflect the history of oscillating acceptance of Complex Systems ideas within the field of archaeology over the last 40 years. In addition, there has been a resurgence and renewed interest in these ideas only in the last 10 years with advances in computational methods. Complex Systems have a large number of interacting, autonomous individuals and exhibit emergent behavior. Such behaviors cannot be interpreted based on the behavior of a single individual (Simon, 1996). Studies using the most current versions of this approach are actively concerned with how bottom-up processes like the interactions of individuals can result in complex organizations, such as centralized hierarchies. An example of this approach is White's (2013) research on the emergence of social complexity in hunter–gatherer systems in eastern North America. Ostensibly, this example addresses the conceptual theme of Social Complexity, however, the angle of research is devoted to disentangling the link between individual behaviors at the micro-scale and their results at the macro-scale of social complexity. The micro-scale consists of robust ethnographic data on how families form and develop among hunter–gatherers that were then used to construct the ABM. The macro-scale is systemic change, or the emergence of quantifiable aspects of social complexity. White (2013:131) states, "In this case, we are trying to understand the relationship between the 'rules' affecting family-level productive and reproductive behaviors at the operational level and the patterns of family size and 'wealth' distribution that emerge at the system level." This has considerable theoretical implications, perhaps still unrealized, for a field that has yet to develop a rigorous way to study bottom-up processes.

Thus, the combination of this conceptual perspective and ABM allows the researcher to experiment with and investigate the interactions of different scales of behavior. This is a profound point for archaeologists—ABM combined with a Complex Systems approach has the ability to accommodate the mismatch between the operational elements of the material record, for which we often have very minute details contained in static snapshots, and global patterns of a social system, information that is much more general in nature (White, 2013).

4.7. Expanding the theoretical scope

ABM is not domain or discipline specific, affording the ability to cross-cut disciplines and theoretical foundations. While ABM is associated most often with particular concepts from Complexity Science and Human Ecology, the choice to use ABM does not require acceptance of any of the conceptual themes already discussed. ABM is a dynamic, flexible, formal modeling methodology in which a number of theoretical paradigms may be explored, as long as the researcher is concerned with the importance of the individual in understanding global patterning. The previous discussion of themes and related case studies demonstrates some of the increasing realization of the scope of this flexibility, however, we can note rather obvious voids in coverage when considered against the grand challenges of archaeology listed earlier. The coverage of themes is skewed toward human–environment interactions and general processes like the development of complexity and away from social, humanistic aspects and the ramifications of individual belief and actions. The non-practitioner archaeologists who are familiar with ABM, have probably been exposed to it through the historical studies mentioned earlier like the Artificial Anasazi or Kohler et al.'s series of publications based on an extensive ABM of the Mesa Verde region of the US (Kohler et al., 2000; Kohler et al., 2007; Kohler et al., 2012a; Kohler and Varien, 2012). Both projects have a social system embedded within a well developed environmental component, but until very recently have not attempted to study the emergence of political complexity (Kohler et al., 2012b, 2015).

In the concluding statement of a recent review, Lake (2014) suggests that "Demonstrating the widespread archaeological applicability of what one might call explicitly 'sociological' simulation remains a challenge." We agree with this statement, however, it is not a limitation inherent to ABM. It is more likely the result of a lack of published examples describing the step-by-step process in framing relevant archaeological social theory within the context of an ABM. Therefore, in the following section we provide an example of the process of integration of an established social theoretical framework relevant to a large body of archaeological researchers—agency, structuration and practice—with the epistemology of ABM. It is an example of the type of critical thinking possible with an ABM, in which social theory can be integrated into the running and testing of the model, and where there is dissatisfaction with the use of social theories as post hoc explanation of archaeological patterns.

5. The collective individual

ABM methodology inherently includes the potential to study individuals and how their actions may contribute to collective phenomenon. Realization of this potential is both facilitated and hindered by theoretical cross-currents over the last 40 years that have reshaped the social sciences, in some cases profoundly. In sociocultural anthropology and related fields, for instance, individual agency has become foundational to interpretation of cultural production and transmission. Focal areas often include cultural meaning production, identity maintenance, and the subjectivities of person and place inspired by social theory of the 1970s and 1980s (e.g. Bourdieu, 1977; Clifford and Marcus, 1986; Giddens, 1984). This work emerged as a reaction to earlier studies of culture as temporally fixed, spatially bounded, and composed of kinship and social categories assumed to function only in a normative way. Further, the rigid categories of traditional ethnography failed to capture cultural dynamics, especially the role of individual actions as imperfect and often impractical, but at the heart of cultural reproduction. The result for contemporary research is a more humanized and dynamic understanding of individuals and their relationship to others and social institutions. These perspectives remain especially influential in sociocultural anthropology, cultural geography, philosophy, gender studies, and cultural studies, and to a lesser degree in archaeology, sociology, economics and international relations, among others. Coupled with new perspectives on individual practice was a far-ranging postmodern critique of research practices across the social sciences and beyond that often rejected positivism in favor of locally situated outcomes (Marcus and Fischer, 1986; Rosaldo, 1993). This was essentially a move away from the objective or authoritative voice in favor of situated narratives (e.g. Behar, 1993).

Archaeological studies have responded to the emergence of individual-oriented theory, although data sources seldom produce the detailed information needed to follow the actions of individuals or small groups. However, theoretical work has conceptualized the idea of collective agency (Bell, 1992), along with an emerging diversity of interpretations including material culture contributions to cultural meaning, identity formation, and fields of action. These perspectives tend to recognize agency as a situated quality of social relationships for interpreting processes of culture change and more localized dynamics (Robb, 2010:494; van der Leeuw, 2008).

The computer science method and theory behind the object-oriented strategies of ABMs starts with single actors or small groups and is fundamentally predisposed to mesh with the perspectives described above (Axelrod, 1997; Henrickson and McKelvey, 2002; Spencer-Wood, 2013). Numerous ABM studies outside of archaeology in the social sciences and humanities have explored the meaningful actions of individual agents, and this work is continuing at an increasing pace (Downey, 2005; Skyrms, 2000; Youngman and Hadzikadic, 2014). However, significant theoretical and methodological divides remain between disciplines. In an influential article Kohler (2000) wrote about rebuilding the social sciences through the potential of ABMs. Kohler noted that it was possible to create strong social simulations by adopting a focus on evolving adaptations, through artificial intelligence and agent learning. Even without building computers as understanding machines, current social simulation methods allow for the study of virtually any of the issues and themes mentioned above.

Realizing potential requires workable methods. Because most ABM studies focus on collective action beyond the individual, or agents as social groups or institutions, there are only three general methods currently useful for analysis of individual agents and their activities: network analysis, narrative, and cyber ethnography.

Network Analysis: ABMs produce dynamic interactions between agents and may include analysis of the resulting networks. However, social network analysis is a separate well-developed field of study with its own theoretical orientation (Borgatti et al., 2013; Cioffi-Revilla, 2014:89-118; Wasserman and Faust, 2006; Watts, 2004). Network analysis is an obvious and natural part of analyzing individual agents and their connections within a social landscape.

Narrative: ABMs can produce narratives that describe the interactions of agents (Sack, 2014). A recent example using small-scale polities (macro-lineages) as the agents, generated a narrative of simulated polity interactions as an analog for comparison with texts written by early Chinese historians from the second century BCE (Cioffi-Revilla et al., 2015:101). A narrative strategy can also be used to explore diversity within the agent population. Not all agent narratives are the same. Unusual agents, such as those that accumulated wealth, might be compared. Conversely "typical agents" might be chosen to explore how norms are maintained in society, or a host of other research questions (Auble, 2015).

Cyber Ethnography: Agent movements and interactions can be tracked within an ABM. For instance, in the case of the HouseholdsWorld model of Inner Asian pastoralists, it is possible to follow a family of simulated pastoralists through their daily and annual movements, record their kin and friend interactions, note their changing herd numbers, observe when their children are born, and when they leave the household to form a new family (Cioffi-Revilla et al., 2010; Rogers et al., 2012). The result is a series of qualitative narratives that can serve many of the same purposes of traditional ethnography. Even without the far-reaching postmodernist critique described above ABM practitioners share a broad realization that individual agents need to be studied in a more meaningful way, not only to validate collective action (Louloudi and Klügl, 2012:1257) but to better interpret the role of individual humans.

6. The way forward: Capacity-building

A basic challenge to the mainstreaming of ABM and other computer simulation techniques in archaeology is a double-edged sword—archaeologists are rarely trained computer programmers. Therefore, not only is the implementation of models constrained, but also the number of people who can evaluate them. Perhaps, the latter is the greater problem since the former can be solved by building capacity through already increasing training opportunities. The lack of experts in an archaeological method is not exclusive to ABM in archaeology; not all of us are trained in the chemistry of isotope analysis but most of us are likely to accept their validity. Instead of evaluating the validity of the method in these cases when we know little about it, we evaluate the logic of the argument and its supporting evidence. ABM ought to be held to this same standard, but for ABM, it has not been clear how to make these evaluations because of two issues: (1) the appropriate uses of ABM in an archaeological context; (2) the mismatched results expected for linear assumptions underlying common archaeological models and the non-linear assumptions inherent to ABMs. The first issue we have tried to redress in the sections above, but the second requires more capacity building.

What do we mean by the mismatch between linear and non-linear assumptions and expectations? In a traditional linear model of cultural change through time, change does not deviate from a linear progression—for example, the Neolithic evolves into the Chalcolithic and then to the Bronze Age and so on, tracked by smooth transitions in material culture. The relationship is linear—the input is a change in technology, the output is a proportional change in social complexity. This is a rather simplistic example and a type of formulation that has been heavily criticized by archaeologists for its inability to account for variation that we know empirically exists, e.g. periods of stability or sudden advances, unique events, or even "devolution." The advantage of linear models is that they are easy to evaluate, but the greater disadvantage is that they can lead to analyses where the complexity that we know exists in the human past is discounted.

ABMs, in contrast, have the ability to examine non-linear processes while capturing qualitative and quantitative features, in the sense that they embrace the complexity and variation inherent in human social systems and eschew general, reductionist laws in favor of plausible explanation. In the Chiefdom model detailed earlier, we discussed an example implementation of non-linearity by including probabilities and uncertainties. In other studies the implications for demography of non-linear outcomes resulting from simulated extreme weather events over long periods of time have been studied using complexity and resiliency theory (e.g. Redman, 2005; Rogers et al., 2012). As such, it is not necessarily appropriate to evaluate these models in the same ways as linear models. Appropriate methods have been developed and tested for ABMs and practitioners do provide a limited discussion of them in their publications, but they are not often highlighted, leaving their models vulnerable to the accusation that "the books have been cooked."

An ABM is essentially an elaborate hypothesis. Fig. 6 illustrates the processes that connect the social system of interest with relevant data, model development, and eventual output. As with any hypothesis the argument may be built through data collection from diverse information sources, ranging from intuition, to qualitative observation, to detailed highly-corroborated "hard" measurements. The model parameters are developed through a process of abstraction. The abstractions are compared against empirical data to assess their validity in a process called calibration. For example, in the HouseholdsWorld model, building population dynamics for the herd animals called for calculating the daily consumption rates for sheep. Based on studies in rangeland management, it was determined that 1.1 kg of dried biomass per day was a reasonable value (Robinson, 2001; Shurentuja et al., 2002; Rogers et al., 2012). Calibration provides the foundation for reliable model results, however, not all parameters can be calibrated precisely, often because no source of empirical data exists. This is especially true for archaeology. Because of the dynamic interactions inherent to ABM it is necessary to test model results thoroughly, even when every parameter is tightly calibrated. Output from the model simulation is tested through a process called "validation."

ABM validation is highly developed and a booming endeavor in a variety of fields, including archaeology, and multiple publications and informal on-line posts for the researcher interested in the step-by-step details of implementation exist elsewhere (see Thiele et al. (2014), for a good primer; for examples of archaeological advances in validation, see Crema et al. (2014a), Kovacevic et al. (2015)). The validation process consists of a suite of tests (Cioffi-Revilla, 2014:236–237) performed to assess the extent to which output from an ABM matches observed records. As stated earlier, ABM practitioners can employ a variety of validation techniques.

Empirical validation tests ABM results against empirical observations (Railsback and Grimm, 2012:238). This process asks the question, do the predictions of the code acceptably represent the real world? This is the most common type of validation used in archaeological publications because it meets the standard expectation of the archaeological research cycle—data, hypothesis, analysis, and empirical verification with data. Most ABM software platforms are equipped with the ability to aggregate a model's results through graphical outputs as well as output to spreadsheets and statistical packages. ABMs that are nonlinear and have inherent stochasticity are described by central tendency measures of multiple, repeated simulations. Stochasticity, the variability between simulation runs resulting from the complex interaction of properties, is a normal quality of ABM.

Fig. 7 illustrates a set of results from the Chiefdoms model. This particular experiment was performed to investigate the possibility of accurately recreating cycling – a typical systemic, organizational behavior empirically recorded for many chiefdoms wherein political organization shifts between simple (one-tier of hierarchy – the chief) and complex chiefdoms (at least two-tiers of hierarchy – the paramount chief, subordinate chiefs or leaders) (Anderson, 1996). Cycling is induced by removing the paramount chief, the most powerful, most connected individual in the system and then observing the resilience of the system to this perturbation. The example results show a comparison of different intervals on the *x*-axis at which the chief was removed from the system. Each removal interval-iteration [5, 100] was run 50 times creating the variation around each removal interval seen in these results. The repeat runs are common in ABM, due to inherent model stochasticity. The boxplots represent the connectivity (links on average) in a simple chiefdom in the model that developed in the aftermath of chief removal at the point in time just before the next removal. To isolate effects of chief removal, population was held at 100 for all simulations. It is tempting to suggest a "breakpoint" at removal interval = 50, where variation in connectivity reaches a minimum if the model is allowed to proceed before the chief is removed for 50 time-steps, or 50 years in this model. Possibly, a chiefdom achieves the most stability (the least variation in connectivity) if it cycles in leadership every 50 years. This matches with the short-lived duration of chiefdoms observed ethnohistorically and archaeologically in the Southeast US, ranging from 50 to 150 years (Cobb, 2003). We might say that this model is one step closer to being validated. This is a brief demonstration of the process and that, in order to make broad comparisons to the US Southeast, further investigation

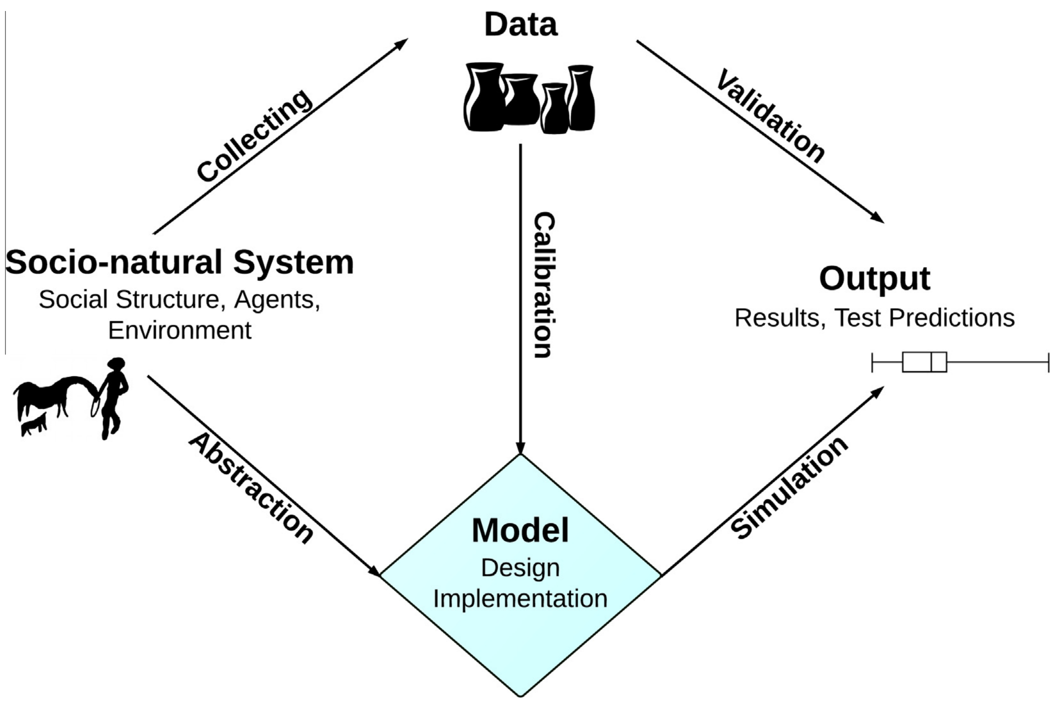

Fig. 6. The process of creating an ABM, from concept to results showing the relationship between the human social system, model design, data sources, and eventual model output. Key actions in the research process are indicated by directional arrows.

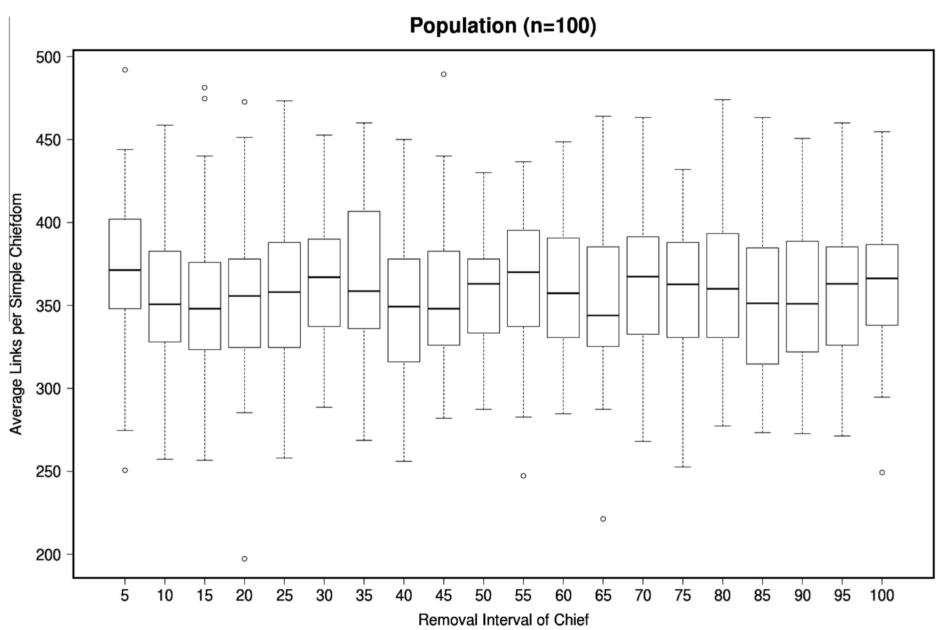

Fig. 7. Example output format of sensitivity analysis results from an ABM ("Chiefdoms and Structural Resilience to Stress," Cegielski, 2010). This shows a parameter sweep on the *x*-axis of different intervals at which the chief, or most powerful individual, was removed from the system. The box plots represent the connectivity (links on average) in a simple chiefdom in the model. Interpretation: It is tempting to suggest a "breakpoint" at removal interval = 50. In other words, variation in connectivity decreases (in fact, reaches a minimum) if the model is allowed to proceed before the chief is removed for 50 time-steps, or 50 years in this model.

would be necessary through a series of different experiments and tests against empirical observations.

Sensitivity analysis may be performed as a second component of testing model output (Thiele et al., 2014). Sensitivity analysis disentangles the complexity of the model and begins to isolate explanatory mechanisms from among the multiple interdependent relationships in play. The basic process is to choose a parameter of which there is some uncertainty about its importance to the pattern of results and then to vary that parameter. If the output is relatively unaffected, then uncertainties about the parameter are less important to understanding the question of interest.

Again, this process can be illustrated with the Chiefdoms model. As seen in Fig. 2, this is a complex, nonlinear, and multi-variate model and thus the causal link between structure and cycling needs to be further demonstrated through sensitivity analysis. If we wish to assert that all chiefdoms are characterized by cycling approximately every 50 years because the nature of the power structure necessitates this in order to preserve system "connectiv-

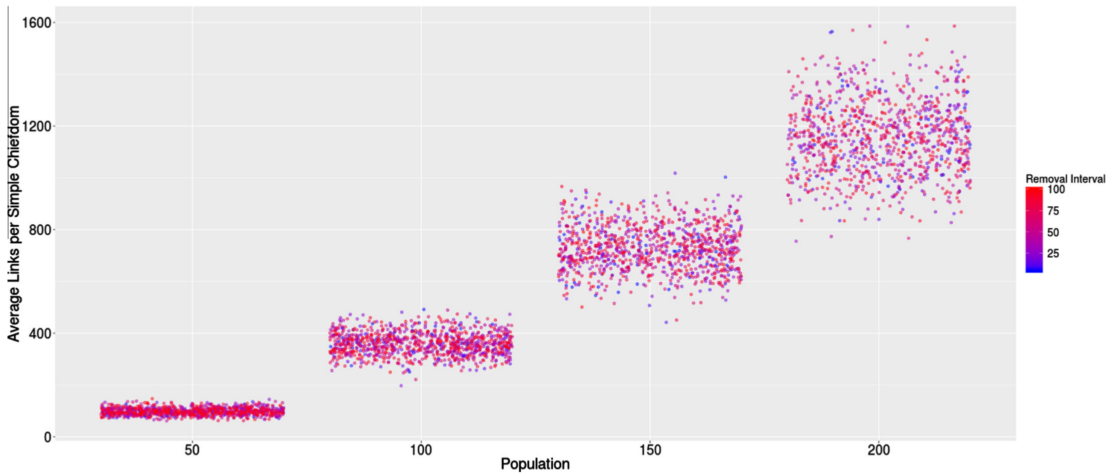

Fig. 8. Results from the same experiment as in Fig. 7, but this time showing a parameter sweep on the *x*-axis over four different population levels. Interpretation: Instead of holding population constant, this set of experiments tested for sensitivity of the relationship between average connectivity within a simple chiefdom and time between removals of the chief to population variation. Two conclusions can be drawn from this: (1) Population has a distinct relationship with connectivity, or Average Links per Simple Chiefdom, but (2) removal interval has no relationship with connectivity, contradicting conclusions demonstrated in Fig. 7. (The distribution of observations color keyed by removal interval is not clearly patterned.)

ity," it might be reasonable to suggest that this behavior should remain robust from the smallest to the largest scale chiefdoms. To test this, the size of the overall population was varied in increments of 50, beginning with 50 and ending with 200, and for each of these increments, removal interval-iterations [5, 100] were run 50 times each as in the previous experiment. As before, connectivity, or Average Links per Simple Chiefdom, was tracked.

Thus, instead of holding population constant, this set of experiments tested for sensitivity of the relationship between average connectivity within a simple chiefdom and time between removals of the chief to population variation. The results of this sensitivity analysis are pictured in Fig. 8. The dots display the connectivity in a simple chiefdom that had evolved by the time step just before the last chief removal of each run as color keyed by removal interval-iteration. Two conclusions can be drawn from the results of this sensitivity analysis: (1) Population has a distinct relationship with "Average Links per Simple Chiefdom", or connectivity, but (2) removal interval has no relationship with connectivity, contradicting conclusions demonstrated in Fig. 7. The distribution of observations color keyed by removal interval is not clearly patterned. This demonstrates exactly how sensitivity analysis leads to a stronger model. There was some uncertainty as to the importance of removal interval to the pattern of results, an uncertainty lessened through sensitivity analysis. The degree of power that sensitivity analysis holds for archaeologists cannot be overstated. We can begin to differentiate and even rank causal factors according to their importance and plausibility. Not only that, we can study several factors at once when we are interested less in the factors themselves and more in their interactions.

6.1. Final observations

Archaeologists are interested in explaining the past lifeways of people, yet at times, ABM journal publications in archaeology (partly due to requirements of publication) provide limited attention to how ABM is being integrated into prevailing archaeological goals and theory in favor of discussions of computational methods, often with "depersonalized language." This is a disjuncture that may be responsible also for the constrained scope of ABM application to archaeological themes typically linked with computational and positivist methods, i.e., environmental archaeology and formation processes. Yet given the preceding discussion, many of the defining characteristics of ABM should make them more appealing to "post-processual" paradigms comfortable with individual agency, irregular variation, exceptions, contextualization, particularism, and contingency (Spencer-Wood, 2013). The archaeological studies noted here are actually an instance of a far broader phenomenon affecting the social, biological, geological, and engineering sciences. Many of the insights being developed in these fields are of direct relevance to archaeological inquiry, in fact, they represent a bridge to broader interdisciplinary engagement. For example, although little used by archaeologists, every issue of the *Journal of Artificial Societies and Social Simulation* includes studies relevant to the themes discussed here.

We argue that ABMs represent an approach that is potentially revolutionary for archaeology. There are also problems that have hindered its adoption. Above we have suggested ways in which many of the concerns may be eliminated. However, it is also worth observing that ABM is not the solution for every problem and there are technical limitations to the methodology (Breitenecker et al., 2015:72-73). For instance, ABMs that construct complex worlds often encounter limitations in the capabilities of both software and computer hardware. This is one reason that very large complex models are rare. As ABMs have grown larger and more complex the computing power of any single computer, even a supercomputer, may be incapable of calculating the hundreds of millions of processes at each time step. Distributed computing, as in a distributed network of computers may be the solution. However, since ABMs are stochastic and increasingly intelligent agents interact with many other agents, the calculations require constant reintegration, meaning that each distributed computer would have to interact constantly, thus defeating much of the benefit. At present, the challenges of very large ABMs are unsolved, although there are important possibilities on the horizon (Payette et al., 2013:3–5; Rubio-Campillo, 2015). Another major challenge is the complexity of the software needed to develop an ABM. Software systems (such as NetLogo) have moved toward easier implementation, however, the skill level needed is still relatively high. Ideally, software systems that allow users to express model content without knowing higher-level programming need to be developed. As we have noted above, the continued improvement of computer technologies and software are likely to make some of these issues less problematic.

We have endeavored also to pry open the lid on the "black-box" and give insight into the internal logic of ABMs and the ways in which they are appropriately validated. The use of ABMs is growing with the advent of user-friendly, open source tools like NetLogo and RePast and integration with analytical software packages like R and with GIS. It is predictable that the number of new archaeologists trained in ABM also will grow within the next few years. We do not propose, however, that all archaeologists learn how to code. In fact, a more profitable avenue is to encourage interdisciplinary collaboration with computer scientists interested in computational applications. Given trends in training and collaboration and the broad applicability of ABM we foresee continued growth in its use, along with better integration with archaeological theory.

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Glossary

This glossary includes key terms used in the article, unless the term is already defined in the text. For a systematic and more complete presentation of terminology related to computational social science and ABMs see Cioffi-Revilla (2014, chapters 8 and 10)

Agent-based model: ABM is a class of object-oriented computational models with three characteristics: a set of actors or agents, an environment and processes specifying how agents interact with the environment and other agents. The agents operate in an environment that may be simple and abstract or exhibit detailed characteristics of specific places and times. An ABM is a description in computer code of how these components work together. ABMs are described in further detail by Cioffi-Revilla (2014), Epstein and Axtell (1996), and Railsback and Grimm (2012). An artificial society or complex society model is often used as another term for ABM. An artificial society model has all aspects of an ABM and would encompass a relatively complete social system (see Epstein and Axtell, 1996).

Agent: Agents are the fundamental components of ABM. Agents are usually analogous to an individual human, but may alternatively be a family, a larger kin or friendship-based social unit, a political organization, a trade union, or some other entity within society. Agents in large-scale ABMs are typically autonomous, unique, change over time, interact with only a subset of other agents, and have goal-directed behaviors. Outside of the social sciences agents may be other types of components of larger systems, such as social insects, organisms in ecosystem research, or cells within a body.

Behavior (of agent): Agents in ABMs are given a set of behavioral processes, such as birth, death, reproduction, decision-making, sharing with other agents, avoid agents from other social groups, and many other potential behaviors typically exhibited by humans.

Calibration: Calibration or "fitting a model to data" is the process of adjusting parameters used in a model. Each parameter in an ABM must be based on at least a reasonable approximation of some aspect of the modeled environment and agents, e.g., rainfall or aspects of human behavior. The approximation may be guided by theory alone (because no real world data exists) or it may be based on a variety of real evidence. If, for example, agents reproduce then the cumulative population birth rate cannot be beyond known human examples. If it is, then the equations used to define the parameter must be reexamined (also see Fig. 6). Parameter sweeps are another form of calibration.

Complex Systems: see Complex Systems Theory

Complex Systems Theory: Complex systems theory emerged in the 1980s through study of systems of interacting entities that embody emergent properties, not part of any one entity. Although less a formal model than a set of shared perspectives, complexity theory features several important characteristics. These include: a hierarchy of organized functions exists within the system, patterns emerge without centralized direction, self-organization occurs, nonlinear interactions at a small scale may have large consequences, systems have boundaries that are poorly defined, and system characteristics are more and different than the sum of the individual components (see Holland, 1998). Dynamic agent interactions in ABMs result in many of the qualities described in complexity theory. The term "complexity" is used extensively in archaeology, but typically not in the sense of complex systems theory.

Complexity Science: see Complex Systems Theory

Computer Simulation: All ABMs are simulations, but not all simulations are ABMs. A computer simulation examines change over time in some aspect of a system and is therefore iterative and process-oriented, but does not necessarily have the agent-oriented characteristics of an ABM. In particular, early archaeological simulations from the 1970s and 1980s were often not as detailed as ABMs but were descriptions of the behavior of the whole (Lake, 2015:10–12; Sabloff, 1981).

Cyber Ethnography: The ability to track agent activities within an ABM to construct narratives comparable to abstract versions of localized ethnography. The purpose is to explore the role of individual agents in the outcomes of the model research questions.

Distributed computing: The process of assigning small segments of a large computational problem to many individual computers, or separate cores within a processor, as in parallel computing.

Emergence: As in complex systems theory, a calibrated ABM may produce patterns and results that were not initially programmed. Emergent properties may be unanticipated and may represent critical findings about the operation of the system. The demonstration of an emergent property is equivalent to a proof in an analytical systems.

Model Output: The results, or output, of an ABM simulation run may be a numerical table, a variety of charts, maps showing distributions, or all of the above. Some ABMs are capable of providing a three dimensional visualization of a landscape with agents as a form of model output.

Network Analysis: Network science analyzes the relationship between "nodes" and "edges" – objects in the network and the connections between them. In archaeology an example might be a trade network, composed of sites (nodes) and the distribution (edges) of goods from those sites. Network science is increasingly used in archaeology and represents an important new set of methods and theories (Collar et al., 2015).

Non-linear: Many social phenomena cannot be explained by the assumptions of a linear relationship. Explanations that assume linear relationships propose that effects are explicitly proportional to their outcomes. A standard regression analysis predicts a consistent relationship between two variables and measures how actual data deviates from that expectation. However, complex human systems involving everything from individual perceptions to patterns of conflict and cooperation exhibit non-linear relationships, such as exponential or logarithmic (Cioffi-Revilla, 2014:225–226).

Optimization: The process of increasing the efficiency of the computer programing code underlying the ABM. Several techniques that simplify the computer code are used primarily to increase the speed of the simulation.

Parameter: A parameter is specification of an aspect of the model derived from data, general information, or theory. In a complex ABM, such as HouseholdsWorld, a parameter may be such things as "social memory of ancestors", "mean number of children per household", "maximum camp size", "biomass growth rate", and many others (Rogers et al., 2012). A parameter is an input to the model believed to be necessary if the model is to successfully address the research questions. The usefulness of a particular parameter is tested through validation procedures.

Parameterization: The process of defining the parameters to be used in an ABM, such as the characteristics of the agents and their environment. This is normally done in the initial formulation of the research design but may need to be revised if the model does not represent the real world well enough to answer the research questions.

Reproducibility: A fundamental concept in science is the repeatability or reproducibility of an experiment as a form of validity and accuracy checking (Popper and Pichler, 2015). In ABMs the use of an ODD and open source archiving of computer code is designed to increase the transparency of the development process and allow others to evaluate and construct the same experiments.

Sensitivity Analysis: A diagnostic approach designed to help determine which parameters have little or no effect and which have a large effect. A parameter with no effect has no explanatory value and may be eliminated (for examples see Railsback and Grimm, 2012:292–297). During validation different values for a parameter may be further compared.

Stochasticity: Because of the dynamic nature of ABMs and the inclusion of many parameters based on a random distribution of values, it is normal for any two runs of the simulation to show variability. This variability is referred to as stochasticity and in the case of archaeological ABMs represents the non-deterministic nature of history. In other words, if we could replay history over and over, it would not turn out exactly the same each time – history is stochastic.

Time-series Dataset: a dataset consisting of information in a chronologically ordered series.

Time-step: In an ABM the simulation proceeds in iterations called steps or time-steps. The unit of time defined in a step depends on the objectives of the simulation. Time-steps are typically, one day, one season, or one year.

Validation: Validation is a process for determining whether model output is a reasonably accurate representation of the real world. There are several techniques for validating a model, including informal inspections of output, static techniques, symbolic techniques, constraint-based techniques, and dynamic techniques: such as white-box testing, bottom-up testing, graphical comparison, predictive validation, and statistical validation (Klügl, 2008; Popper and Pichler, 2015; Xiang et al., 2005; also see Fig. 6). Simulation systems such as Netlogo, MASON, and Repast each have several facilities for conducting validation tests (Cioffi-Revilla, 2014:237).