Computational Models of Collective Behavior

Robert L. Goldstone

Marco A. Janssen

Indiana University

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Correspondences should be sent to: Dr. Robert Goldstone

Psychology Department

Indiana University

Bloomington, IN. 47405

812-855-4853

rgoldsto@indiana.edu

Abstract

Computational models of human collective behavior offer promise in providing quantitative and empirically verifiable accounts of how individual decisions lead to the emergence of group-level organizations. Agent-based models (ABMs) describe interactions among individual agents and their environment, and provide a process-oriented alternative to descriptive mathematical models. Recent ABMs provide compelling accounts of group pattern formation, contagion, and cooperation, and can be used to predict, manipulate, and improve upon collective behavior. ABMs overcome an assumption underlying much of cognitive science – that the individual is the critical unit of cognition. The advocated alternative is that individuals participate in collective organizations that they may not understand or even perceive, and that these organizations affect and are affected by individual behavior.

Cognitive scientists tend to focus on the behavior of single individuals thinking and perceiving on their own. However, interacting groups of people also create emergent organizations at a higher level than the individual. Interacting ants create colony architectures that no ant intends. Populations of neurons create structured thought, permanent memories, and adaptive responses that no neuron can comprehend by itself. Similarly, people create group-level behaviors that are beyond the ken of any single person. The emergence of higher-level organizations from the interactions of lower-level units is surprising in the case of group behavior because we are the lower-level units, and the higher-level organizations typically emerge spontaneously, without our knowledge. Social phenomena such as rumors, the emergence of a standard currency, transportation systems, the World Wide Web, resource harvesting, crowding, and scientific establishments arise because of individuals' beliefs and goals, but the eventual form that these phenomena take is rarely dictated by any individual.

There is a growing realization across the social sciences that one of the best ways to build useful theories of group phenomena is to create working computational models of social units (e.g. individuals, households, firms, or nations) and their interactions, and to observe the global structures that these interactions produce. In the last couple of years, the use of computational models of collective behavior has grown tremendously in sociology [1], economics [2], psychology [3, 4], and anthropology [5]. This approach is relevant to cognitive science because it integrates computational modeling and understanding human behavior. This relevance is timely because these models provide balance to cognitive science's bias to view cognition as a property of an individual mind rather than as resulting from interactions among people and their environments [6].

We will focus on computational models called Agent-Based Models (ABMs), which build social structures from the "bottom-up," by simulating individuals by virtual agents, and creating emergent organizations out of the operation of rules that govern interactions among agents [7-8]. ABMs have a number of attractive features that supplement traditional methods for exploring group behavior. First, they are expressed with unambiguous mathematical and computational formalisms so that once they have been fully described, their predictions are clear, quantitative, and objective. Second, they provide true bridging explanations that link two distinct levels of analysis: the properties of individual agents (e.g. their attributes and interactions), and the emergent group-level behavior. When successful, agent-based models are particularly satisfying models because they show how coherent, group-level structures can spontaneously emerge without leaders ordering the organization, and sometimes despite leaders' effort. Third, because the models are typically either simple or informed by real-world data, they are appropriately constrained and cannot fit any conceivable pattern of data. The self-organization process itself exerts strong constraints on the kinds of patterns likely to be observed [9]. In this review of ABMs, we will characterize the approach; describe critical decisions that a modeler must make; present case studies of ABMs from literatures on organization, contagion, and cooperation, and assess the future opportunities and challenges for ABMs.

Characteristics of Agent-Based Models

ABMs tend to possess four characteristics:

Computational description is at the level of agents. ABMs consists of a large number of interacting agents, operating within an environment. Each agent's behavior is governed by rules triggered by their local condition rather than global information [10]. High-level summary descriptions emerge from the unfolding agent interactions, but they are not explicitly programmed.

Stigmergic interactions. Agents act on and are influenced by their local environment.

Stigmergy is a form of indirect communication between agents that is achieved by agents modifying their environment and also responding to these modifications [11], e.g. ants following pheremone trails left by other ants [12]. Analogous stigmeric effects are achieved by "swarms" of humans that make a terrain more attractive to others by creating paths with their own steps [13-14], book recommendations on Amazon.com based upon similar readers' buying habits, or robots that created large-scale architectural structures even though they cannot directly communicate, by reacting to and building upon structures left by others [15].

Autonomy of agents. Each agent is capable of autonomous behavior, and possesses individual, albeit frequently simplified, representations of beliefs, goals, and strategies [16]. Agents typically do not calculate optimal or rational courses of action, but rather use heuristics [17-18], reinforcement learning [19], opportunistic adaptation [20], or cross-generational evolution [21] to change their strategies.

Spatially Distributed Populations of Agents. ABMs often consist only of agents and a 2-D or 3-D landscape of environmental "patches," both of which may have a number of attributes [10]. The visuo-spatial and animated nature of the resulting simulations makes the most of people's natural aptitude for visual pattern recognition.

Idealized and Detailed Models

The most fundamental decision an ABM researcher makes is how detailed their model will be. Many researchers purposefully choose to create highly idealized models that boil down a collective phenomenon to its functional essence. Researchers pursuing idealized models are typically motivated to describe domain-general mechanisms with a wide sphere of application. A good example of this strategy is Robert Axelrod's Culture Model [22]. The goal of this model is to explain how beliefs or attitudes converge/diverge in a population over time.

Agents are placed at fixed locations within a 2-D grid, and initially have random trait values on each of several features. The likelihood of neighboring agents interacting with one another is proportional to their similarity across all features. When agents interact, one of the trait values of one of the agents is copied to the other agent, in a process that simulates cultural imitation or social influence. Over time, spatial clusters of like-minded agents develop, although some diversity of opinion is often maintained as dissimilar agents are unlikely to interact even if they are neighbors (see Figure 1). This simple model can explain 1) the spatial clustering of opinions, 2) bandwagon effects, and 3) the spontaneous division of a culture into sub-cultures. The "similarity begets even more similarity" dynamic has application to the spread of smoking in teenagers [23] and geospatial political patterns [24], to take just two examples. The original Culture Model has given rise to follow-up simulations showing how the Culture Model can be extended to disseminating solutions to objective problems rather than opinions [25], incorporating global media rather than only neighbor-to-neighbor interactions [26], and also analyzed to show rapid phase transitions from disordered to ordered configurations of opinions [27]. The Culture Model may be too simplified to fully explain any specific real-world pattern of opinion spread, but it also formally captures an essential commonality of many situations in which homogeneity within cliques co-exists with striking heterogeneity across cliques.

Other ABMs are intimately tied to a specific domain because they include a considerable amount of detail derived from real world data sets and their goal is answering a specific real-world question. One such question is, "Why did the Anasazi people of southwestern United States abandon their homeland around 1350 AD?" To find the answer, research teams [28-29] have developed ABMs that incorporate features grounded in historical records: maize production levels, ground water reserves, the 3-D geography of the Anasazi's Long House Valley homeland, populations established from archeological digs, and social trends regarding child-birth age, the average age of children leaving home, and food consumption needs, all based upon recent maize-growing societies of Pueblo Indians descended from the Anasazi. Specific runs from the eventual model [29, see Figure 2] capture aspects of the rise and fall of the Anasazi population for more than a millennium period from A.D. 200-1300, although the modeling would have been even more impressive if it had been systematically compared to alternative models.

The juxtaposition of these models allows us to critically assess the costs and benefits of idealized and detailed models. When successful in isolating a universal pattern, idealized models have widespread application to many real-world domains, and generate comprehensible explanatory accounts by focusing on only a few critical causal elements. Revealing idealized models have been formulated for the diffusion of innovations [30], collective action [31], the transmission of cultural elements over generations [32], the development of social conventions [33], and language change [34-35]. The downside of these idealized models is that they may map onto no actual case study without extensive tailoring, and they may oversimplify to the point of leaving out crucial details [36]. By contrast, detailed models hold the promise of making faithful predictions by being grounded in a case's particular data. There are ABMs that effectively incorporate considerable detail about university tenure systems [37], electricity markets in England [38], and hunting behavior in eastern Cameroon [39]. The downside of detailed models is that they may be able to predict too many possible outcomes if they have many parameters that are insufficiently constrained. If the models become too detailed, they may become as complex as the modeled phenomenon itself, and hence serve as poor explanatory aids. Given these considerations, our general advice is to choose the level of model detail based on the 1) importance of predicting future behavior in a particular case study (advocating detail), 2) importance of generalizing the model's behavior to new scenarios (advocating idealization), 3) difficulty in assessing what elements of a case study are crucial versus inconsequential in determining the global behavior (advocating detail), and 4) desire for a concise and comprehensible explanatory account (advocating idealization).

ABMs and Aggregate Models

The ABMs described above all work by synthetically constructing virtual versions of social phenomena from low-level descriptions of the individual agents. This approach is in contrast to descriptive models, which use equations to describe aggregate level phenomena. To create tractable descriptive equations it is often necessary to make misleading assumptions that fail to capture essential aspects of natural phenomena. One example is the Mean Field Approximation, according to which all individuals in a group are assumed to be in the same location and experience the same local environment. ABMs that incorporate space and local variability frequently produce much more realistic models. For example, giving agents unique rather than aggregate positions has proven invaluable in modeling the continued stability of host-pathogen populations [40] the genetic diversity in a population [41], and preserved pockets of cooperation surrounded by defectors [42-43]. More generally, ABMs often provide more satisfying accounts than purely descriptive approaches because they posit mechanisms by which aggregate qualities emerge.

Three Core Topics for Agent-Based Models

Three prevalent themes for computational models of collective behavior have been: spatial and temporal patterns, social contagion, and cooperation. The human agents in these models are represented by a wide range in complexity, from particles to simple rule-following devices to rich cognitive architectures.

Patterns and Organization

Political economist Thomas Schelling is one of the founders of computational models of collective behavior in the social sciences, although his original experiments on segregation were done by hand with dimes and pennies [44]. Schelling created agents belonging to two classes (his dimes and pennies) that are reasonably tolerant of diversity and only move when they find themselves in a clear minority within their neighborhood, following a rule like "If fewer than 30% of my neighbors belong to my class, then I will move." The agents still divide themselves into sharply segregated groups after a short time, even though no individual is motivated to live in such a highly segregated world. The work of Schelling stimulated the development of other models of sorting where micromotives lead to surprising macrobehavior especially within political economic processes [43,45].

Recently, a number of physicists have used simulation models to study patterns that can emerge when many humans interact, including human trails [13], traffic jams [46], Mexican waves [47] and panic behavior of pedestrians [48]. In these models humans are represented as particles with variation in speeds or position, and without any requirement of cognition for the agents. In some applications of financial markets, agents are explicitly called "zero intelligence agents" to show that full rationality is not required to explain observed patterns in economic statistics [49]. These simple reactive agent-based simulation models have often provided surprisingly apt account for empirically observed behavior.

Contagion

Social contagion is the spread of an entity or influence between individuals in a population via interactions between agents. Examples are the spreading of fads, rumors, and riots. Computational approaches to simulate social contagion are based on thresholds models [50]. Each agent has a threshold, that when exceeded, leads the agent to adopt an activity. This threshold represents the number of other agents in the population or local neighborhood following that particular activity. Threshold models can be either deterministic [51] or stochastic [51]. Recent work in this area assumes that thresholds are applied to the adoption rate within a local neighborhood, rather than the whole population [52,53]. This has led to the study of the impact of different social network configurations on contagion [54,55].

Cooperation

A social dilemma is a situation where sub-optimal group outcomes are achieved if all agents do the action that is optimal for themselves. If self-centered rational agents do not cooperate in social dilemmas why do we often find cooperation in actual case studies? From an ABM perspective, are the roots of cooperation in the model of the individual, environmental conditions, or information exchange between agents? Robert Axelrod pioneered the use of computational models by showing that strategies which lead to conditionally cooperative behavior are effective in a tournament of repeated prisoner dilemma games, giving better overall performance than uncooperative strategies even though in head-to-head competition with non-cooperative strategies, the non-cooperative strategies prevail [56]. This work led to a large literature on extensions of the original models to include the addition of space [57], indirect reciprocity [58], and more complex strategies [59]. Most of this work uses simple reactive agents. Some recent studies [60,61] focus on more cognitively sophisticated agents with designs informed by psychological theories, such as social comparison and bounded rationality.

The Future of Computational Models of Collective Behavior

These early explorations have given us enough data to make some prescriptions for the development of the next generation of ABMs.

Limitations of current models

Painting in broad strokes, we find a number of limitations with the current crop of ABM models from a cognitive science perspective. We have four recommendations for realizing the promise of ABMs:

Genuine predictiveness. If the first generation of ABMs can be characterized as generally "post-dicting" existing data, the next generation should aspire to genuinely predicting the outcome of future patterns of collective behavior.

Create a computational Lingua Franca. Early work with ABMs has been somewhat unsystematic, with different researchers developing idiosyncratic systems. One result has been the lack of replicability of some ABM results. For example, early demonstrations of the persistence of cooperation in a spatial Prisoner's Dilemma game [57] have been shown to hinge crucially on the unstated assumption of agents that update synchronously (e.g. all at the same time) rather than asynchronously [62]. If ABM modelers all use the same simulation environments, then interesting differences between models can be missed [63], but establishing common modeling methods will promote comparison between models, improve replicability of results, and facilitate researchers' efforts to build upon prior work.

Greater synthesis between experiments and models. When ABMs have been compared to empirical data, they have often been applied to case studies. A problem with case studies is that they are not genuinely replicable events, although role-playing games can sometimes capture their major elements. Instead, we recommend validating ABMs against data obtained from experiments. Ideally, laboratory experiments, field observations, and computational models will not only be integrated, but they will inform and improve one another over several iterative cycles. Relatively simple laboratory situations can be constructed to involve groups of people interacting in idealized environments according to easily stated game rules. Experiments can bridge the often-noted [36] gap between computational models and group behavior because the assumptions underlying the experiments can be tailored to correspond almost exactly to the assumptions of the computational models, and so the models can be aptly applied without sacrificing the concision of their explanatory accounts.

Greater sophistication of internal representations of agents. The majority of current ABMs incorporate rather impoverished representations of agents. Often, each individual is represented by a single, albeit time-varying, number (e.g. "Probability of cooperation=0.8") [3]. In more complicated models, agents are represented by a vector of independent values across a set of dimensions [22]. Actual knowledge has much richer structures than either of these representations. For example, an evolutionary theorist has concepts about natural selection, sexual reproduction, and genetic variability within a population, but these concepts are not independent elements, but rather support and contextualize one another. Concepts gain their meaning by their relations to other concepts [64]. Finding a good balance between incorporating these influences and achieving constrained and elegant models is an excellent challenge for ABMs. If each person is to be modeled as a conceptual network, then a social group is to be modeled as network of networks. From a modeling perspective, the intellectual interest is in the study of how these two levels of networks interact [65]. Communicating is not simply transmitting individual concepts. Communication involves aligning the conceptual systems of agents [33]. One implication of this alignment process is that as concepts migrate across people, they will be systematically altered to fit their owners' conceptual network.

Opportunities

Despite these challenges to current ABMs, the future looks bright for computational modeling of collective behavior. We highlight three opportunities for future modeling efforts.

Modeling Large-scale Collectives. Recently, there has been a phenomenal increase in archival data on groups. Archival data available from on-line news groups, blogs, social network services, chat groups, and topical communities can effectively be used to explore naturally occurring coalition formation, idea spread, and group evolution [66].

Computational Models as Test-Beds. Computational models of collective behavior can explore in advance the possible consequences of public policy changes. ABMs can be used to address "what if" scenarios like "What is the consequence of the spread of HIV if policies are implemented to affect stigmatization of HIV infected persons?" and "What would be the impact on world demographics if parents can choose the sex of their child?" As computational simulations become increasingly realistic, they will serve as increasingly useful test-beds for exploring potential consequences of public policies that have complex, non-linear dynamics.

Group Control Through Indirect Manipulation Rather Than Explicit Rules. Perhaps the most common method of crowd control is through direct orders or laws. If we wish to direct pedestrian traffic, for example, we may institute rules or physical barriers that prohibit certain movements. The cost of such prohibitions is decreased pedestrian morale and the perception of excluded possibilities [67]. ABMs suggest an alternative method of crowd control by changing the structure of the environment such that certain behaviors are facilitated while others are indirectly hindered without instituting physical or abstract barriers. Small changes in environments can often have a major change on the flow because of the positive feedback involved in individuals following other individuals. The need for direct force is reduced by this approach. As we gain confidence in our computational models, they will provide useful advice for not only predicting, but controlling, collective behavior.

Conclusion

There are exciting opportunities for recent efforts in ABMs to both benefit from, and inform, cognitive science. ABMs can benefit from the advanced statistical tools and empirical methods that cognitive scientists have developed for assessing the quality of the fit between computational models and the world. The emphases of cognitive science on neural and cognitive constraints, replicability, comparison between models, laboratory-controlled validation, and realistic cognitive processes of individual decision makers are much needed insights for the ABM community. Conversely, ABM methods advance cognitive science by providing a generative, proof-by-construction approach to understanding social behavior. Cognitive scientists often act like individuals are the sole loci of organized thought, but ABMs remind us that organized behavior can be described at multiple levels, and that our thoughts both depend upon and determine the social structures that contain us as elements.

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Box 1: Questions for Future Research

What are the mechanisms by which individuals within groups learn to cooperate, compete, spontaneously specialize and divide labor, form coalitions, distribute resources, propagate innovations, create social networks, and coordinate complex activities?

How is the gulf between the real-world complexities of social interaction and the relative simplicity of ABMs best bridged: by creating simplified experimental environments that constrain human interaction, by incorporating as much real-world data into ABMs as possible, or by identifying critical real-world elements and selectively incorporating only these into ABMs?

When can models inspired from physics be effectively used to explain collective behavior, and when must the humans-as-particles idealization be enriched to incorporate people's beliefs, memories, plans, strategies, and creativity?

Can ABMs be successfully used to advise organizational design or public policy, for example, by predicting the implications of new voting or auction rules before they are publicly implemented?

Author Notes

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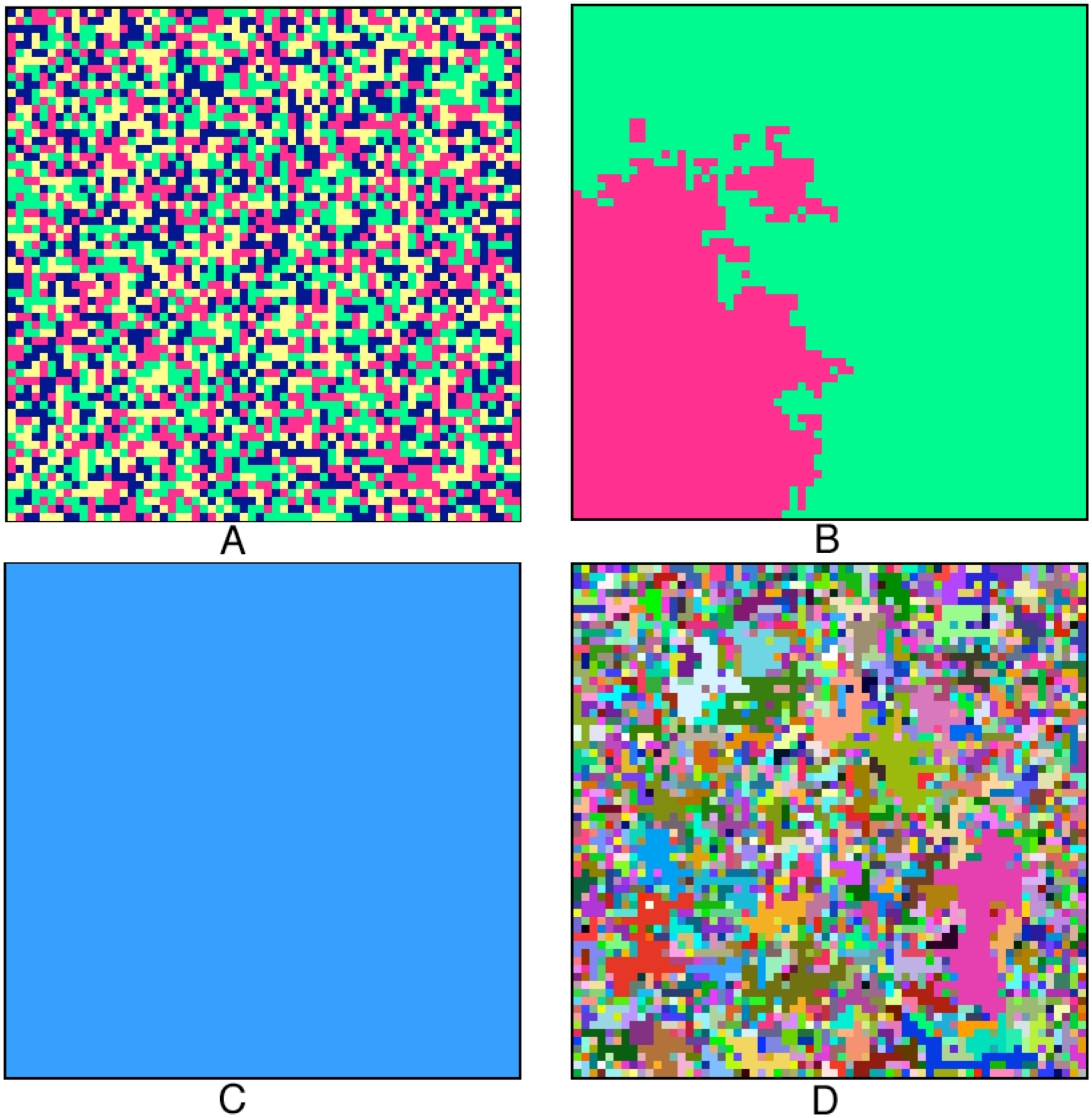

Figure 1. Four simulations of Axelrod's Culture Model [22]. Each agent is represented by a color that represents their entire set of features (e.g. hobby) and trait values (e.g. chess, badminton, violin). Agents with identical colors have identical traits. A) an initial, randomly generated population of agents, each possessing two traits (T=2) on

each of two features (F=2). B) The same population after 4000 generations of interactions in which neighboring agents copy each others' traits, with the probability of interaction proportional to the agents' similarity. The population is frozen because the red and green agents have no traits in common and hence will never interact. C) After 4000 generations, a simulation starting with agents characterized by two trait values (T=2) along fifteen features (F=15). Increasing the number of features, increases the probability of a homogeneous, like-minded population emerging. D) When F=3 and T=15, the population quickly becomes frozen into small cliques that have no cross-group interactions. Increasing the number of traits per feature decreases the size of cliques. A web-based simulation of the Culture Model can be found at http://www-personal.umich.edu/~axe/.

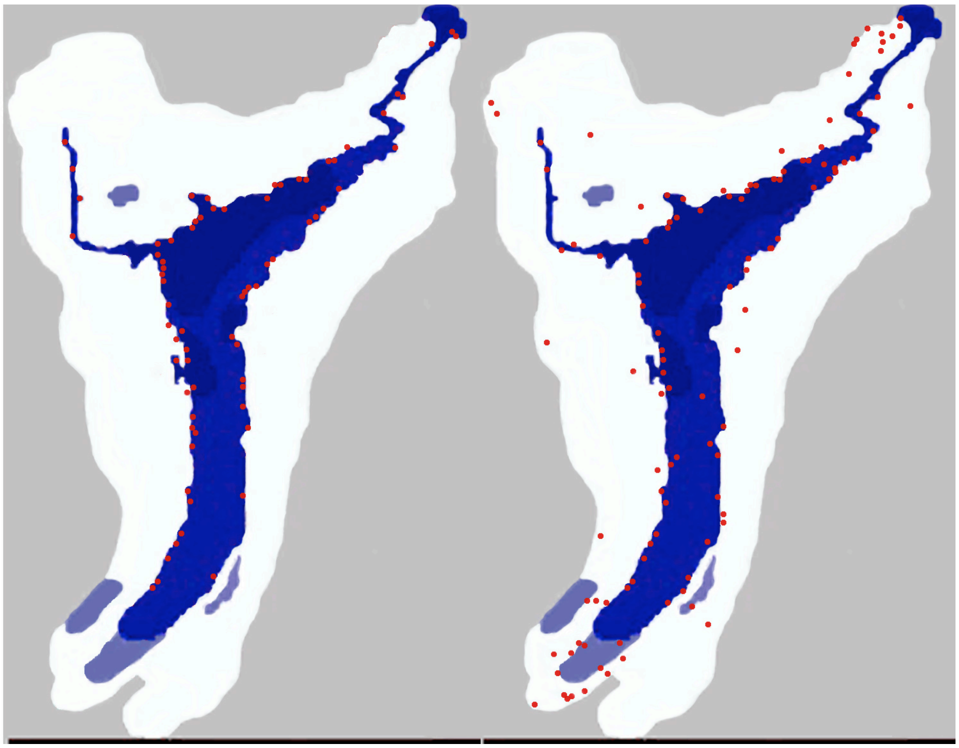

Figure 2. Simulated (left) and historical (right) patterns of settlement for the Anasazi in the Long House Valley around A.D. 1125. Red circles indicate settlements, and the shade of blue depicts the annual groundwater level for a location. This figure was adapted by Rowan Johnston from [29] with permission from the author and publisher.