Title: Understanding Small-Scale Societies with Agent-Based Models: Theoretical Examples of Cultural Transmission and Decision-Making

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Abstract

Formal modeling and simulation methods employing agent-based modeling (ABM) continue to grow in their application and study of human behavioral dynamics at a variety of population, spatial, and temporal scales. Research that uses this perspective spans over a wide range of interests, from cultural evolution to the emergence of cooperation.

This paper explores some of the problems and challenges of using ABM to study common research problems involving small-scale societies. Methodological and implementation benefits relevant for exploring small-scale societies are discussed. We then discuss two simple and research-oriented models created to examine key aspects of social interaction: a) decision-making processes and b) social learning. The intent is to, therefore, provide researchers with clear and useful examples to understand and explore ABM methodology for their own work.

The models are made freely available in four common programming languages and modeling platforms (R, Python, Repast Simphony, and NetLogo). This allows us not only to explore key concepts in modelling human behavior, but also to demonstrate practical ABM implementation in various free and open source tools.

Keywords:

Agent Based Modeling, small-scale societies, cultural transmission, decision-making processes, computer simulation

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1 INTRODUCTION

The popularity of Agent-Based Modeling (ABM) in addressing numerous social science questions is understandable given the operational advantages of studying societies from a bottom-up perspective (Gilbert 2008). Here, we use ABM to mean computer simulations where heterogeneous entities encapsulating decision making processes interact over a given temporal interval. This basic framework is used to experiment with societies of autonomous agents modeling individuals and organizations that interact following nonlinear dynamics. The local behavior and interactions of agents can generate emergent system-level properties, that in turn affect individual agents, thus linking individual behavior to large scale population patterns (Macal and North 2005). This has made ABMs increasingly popular for studying a variety of emergent social evolutionary characteristics in small-scale societies (e.g., Read 2003, Smith and Choi 2007). Such societies are of interest to researchers for understanding a wide range of topics that include prehistoric transfer of technologies or how modern small-scale societies may interact in an interconnected, globalized world (Jackson 1984, Boyd and Richerson 2009, Ruiz-Mallén et al. 2013, Henrich 2004). Overall, the application of ABMs in the study of small-societies provides an avenue to test and explore different social behavioral assumptions and understanding affecting how such societies evolve). Typically, researchers find that lower densities of population can affect key aspects in understanding small-scale societies, such as cultural transmission, leading to debates in the research literature (Henrich 2004).

There are growing efforts to standardize ABM practices (Grimm et al. 2010) in order to make them more accessible or easier to implement (Ozik et al. 2013). This should facilitates commonalities in methodological implementation, facilitating comparability and evaluation of models, and expanded use of ABMs, allowing for greater knowledge transfer. Additionally, that the publication of model code as practical examples of model-based research can also provide useful demonstrations to potential users of how such models are created and implemented. Implementing the same conceptual model in multiple platforms, can cater to different users and make ABM more accessible to a wider research community. Here, we present and discuss example ABMs, in multiple computing languages and platforms, that address common themes for small-scale societies.

The paper begins by briefly introducing formal modeling in the context of ABM and small-scale societies. To demonstrate how one can address challenges of modeling and understanding small-scale societies using ABM, we present several implementations of two models that deal with cultural transmission and decision-making. These two examples cover a wide-range of possible case studies that might be of interest for researchers, making them applicable for study. The models are implemented in the widely used languages/platforms of: R (R Development Core Team 2014), Python (Python Software Foundation 2015), Repast Simphony (North et al. 2013) and NetLogo (Wilensky 1999). All four languages/platforms are increasingly used in scientific computing, and have large active development communities. These tools are also all free and open source, making them particularly attractive for model implementation for a wide variety of researchers. We then present results and discuss these two models with respect to research problems in small-scale societies. We conclude by summarizing the benefits of the models presented and the wider advantages of using this paper’s models for learning about ABM and its implementation.

2 MODELLING SMALL SCALE SOCIETIES

By small-scale societies, we mean societies that maintain social and political autonomy at the level of one or few local communities, thus involving at most a few thousand individuals (Smith and Wishnie 2000). This small group size has a deep impact on cultural systems. They are often based on self-sufficient subsistence strategies (i.e., hunter-gatherers, small-scale agropastoralism) characterized by reciprocal exchange and low population growth (Bodley 2012). Beyond this, population size groups tend to fragment without specialized institutions that characterize much larger societies (Henrich et al., 2010).

The overwhelmingly greatest part of the human past was spent in small-scale societies, making these 'natural' human social forms of particular interest for understanding most of human biocultural evolution (Roscoe 2009). At a fundamental level, that organizational features of our modern hypersocial societies emerged from a small-scale basis.

As noted above, the relatively low number of interacting individuals and lack of cross-cutting and hierarchical social institutions make studying and modeling fundamental human social processes potentially more tractable in a small-scale context. However, empirical validation of models of social processes in small-scale societies is difficult as they only exist today as highly integrated components of much larger social forms that dominate the world, or as vestigial remnants existing on the margins of complex agro/urban societies.

There are several features of small-scale societies that have significant impacts on the dynamics of cultural (and biological) processes, that are of interest for human biocultural evolution but complicate the direct application to the modern world of insights gained from the study of humans in this ancestral social context. First, small populations affect stochastic processes of cultural transmission in a several ways. When societies are divided into small populations that are relatively isolated from each other, founder effects become more pronounced, leading to greater homogeneity within small groups and more heterogeneity between groups. Consequences include the potential for loss of practices and technologies that depend on cumulative cultural knowledge within a particular group and reduced rate of innovation at the regional level, processes that have been demonstrated through computational and mathematical modeling, and observed empirically (Kline & Boyd 2010; Powell et al. 2009). Related to this, the diversity of selectively neutral innovations that can be maintained as a result of drift is largely a function of the size of the population of potential learners and teachers. In a social world in which overall population densities are low and information exchange between small groups is limited, we might expect overall low cultural diversity and slow rates of change.

Second, many small-scale societies are characterized by much higher degrees of mobility than is the case for highly sedentary, complex societies (our modern digitally connected world excepted). This is certainly true for hunter-gatherers but also is the case for small-scale agriculturalists, many of whom practice swidden cultivation, and pastoralists. The amount of mobility can vary, of course, from small-holder farmers (and some hunter-gatherers) who spend months or years in a single locale to residentially mobile hunter-gatherers who regularly move their households on the order of weeks or months (Kelly 1995; Grove 2009). This movement can significantly counteract the effects of small group size on cultural and biological transmission (Powell et al. 2009). Such residential movement gives small groups the potential to greatly expand the pool of potential learners and teachers. In effect, it transforms a landscape of low density small groups into a small world network in which any group has access to the knowledge, or genes, of many other groups with only very small degrees of separation. This has profound effects on rates of biocultural transmission and change, as has been shown in recent modeling experiments

(Barton & Riel-Salvatore 2012; Barton et al. 2011). One expectation would be that as sedentism increases, with decreased reliance on hunting and gathering of geographically shifting resources, declining mobility effects should increase founder effects and decrease innovation rates. This trend would reverse again as regional populations become denser and more socially integrated in complex, urban societies.

Finally, small-scale societies tend to have organizationally simple decision frameworks, emphasizing bottom-up, consensus-based decision-making. Small scale societies tend to operate within the limits of Dunbar's number (Dunbar 1992, Zhou et al. 2005), where most decision-makers know each other on a personal level, and where decision-making bodies of 5-10 individuals optimal for consensus (Johnson 1982) can be assembled without recourse to multi-level social hierarchies. This has made such societies attractive for the application of optimization and game theoretical approaches of human behavioral ecology, and equally amenable to rule-based agents of computational models. As with the characteristics reviewed above, this makes modeling decision-making in small-scale societies particularly valuable for understanding human social evolutionary history, but of more limited applicability to aspects of complex societies where hierarchical decision-making and social control dominate.

Here, we exemplify fundamental cultural processes of information transmission and decision making in the context of small-scale societies, using computational (agent-based) models. We use abstract, rather than realistic, models but do so under conditions described above that characterize small-scale societies: variable, but generally low, population densities of mobile agents that engage in bottom-up decision making and lack hierarchical organization.

3 DECISION-MAKING PROCESSES

The study of decision-making processes has grown especially in the second half of the 20th century under the umbrella of behavioral sciences. The influential work of von Neumann and Morgenstern on game theory (1944) served as a foundational formal model on how individuals choose their actions, based on their knowledge, options and other people involved in given social situations. Several contributions from diverse fields (psychology, economics, biology, anthropology) have extended and critiqued this initial model, which is based on the potential utility that a given strategy has for each individual.

All these approaches combine theoretical models of decision-making with empirical evidence collected from a range of experiments and observations. In this context, simulation has been a key research methodology since Schelling's (1971) segregation model, which is probably the first conceptual ABM, even though it was not executed in a computer. Considering the difficulties of conducting social decision-making experiments with real individuals, ABMs have been used as virtual laboratories to explore and test hypotheses or explore questions under variable scenarios, including dynamics of competition and cooperation (Axelrod 1997a), collective action (Goldstone & Janssen 2005), avoidance of social dilemmas (Gotts et al., 2003), the use of Artificial Intelligence to model complex decision making (Francès et al. 2014) and the relevance of cognitive factors (Conte & Castelfranchi 1995).

A majority of ABMs designed to explore decision-making processes in fact exhibit many characteristics of small-scale societies. Specifically, they combine low densities of non-specialized agents with a lack of formal institutions and foraging subsistence strategies. This is precisely the type of society defined in the Sugarscape model (Epstein & Axtell 1996), which has been repeatedly used as a basis for further work on decision-making studies.

The first model presented in this paper illustrates how ABM can be used to explore decision-making in the context of a heterogeneous environment (ODD document for the model available as **Appendix 1**). This has been one of the most popular applications of ABM (Axtell et al. 2002, Nonaka & Holmes 2007, Gustafson & Gardner 1996, An 2012). In particular, we will examine how variations in agents' mobility can lead to the emergence of the tragedy of the commons (Hardin 1968).

3.1 Model description

Consider a bounded discrete spatial grid with dimensions *xDim* × *yDim.* This zone represents a heterogeneous resource landscape where the cell in each set of coordinates (*x* and *y*) is defined by the current level of resources it contains (*resources*) and a maximum level (*maxResources*). This level will increase every time step following a fixed value (*resourceGrowthRate*) up to the local *maxResources*, and will be decreased if agents consume them. The environment is initialized with random *maxResources* values for each cell in the interval (0,*maxEnergy*) and current *resources* equal to *maxResources* (see **Figure 1** for an example and **Table 1** for the definition of the parameters).

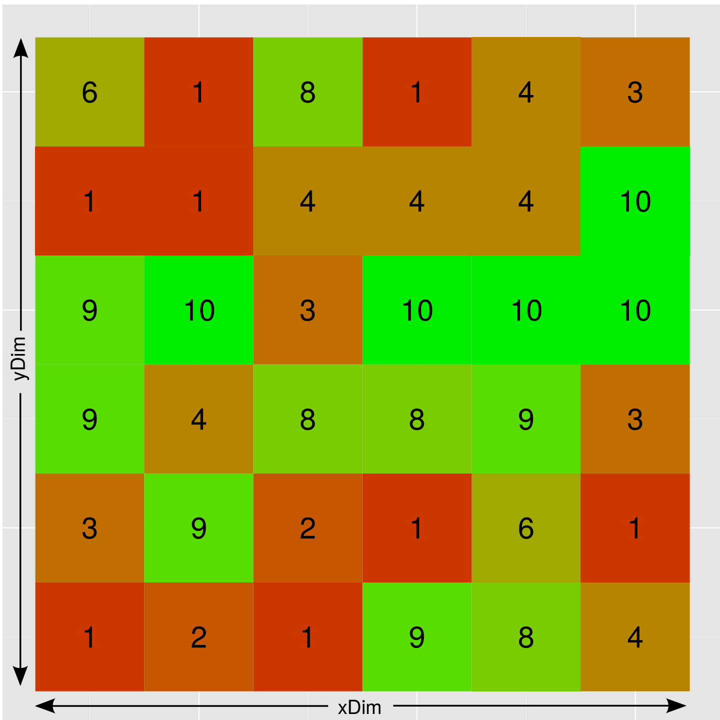

***Figure 1** Example of environment for the decision making model with dimensions xDim/yDim = 6 and resources between 1 and 10.*

This environment is populated by agents, each defined by a spatial location (*x* and *y*), and its current level of energy (*energy*). Every time step this level will decrease by a fixed cost (*energyCost*) and will increase by the amount of resources that the agent can collect from the environment.

This model is initially populated by *nAgents* located at random spatial coordinates. The simulation then proceeds with a discrete number of time-steps, each where the following process updates the population of agents and the resources in the environment:

1. **Decision making** - All agents move to a new location based on a greedy decision making process: each agent will move to the cell with highest *resources* within *radius* of its current location *(x,y).* Chebyshev distance is used to define the list of candidates (i.e., the greatest distance of the two dimensions, *x* and *y*). **Figure 2** shows an example of the process.

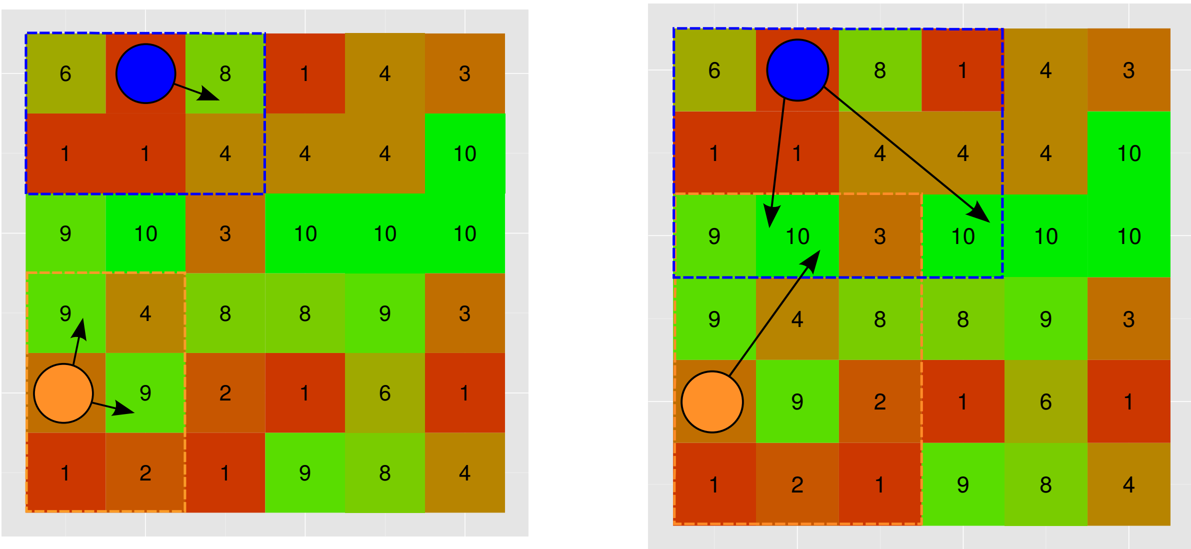

Figure 2 *Decision making for two greedy agents. At time step 0 Blue agent is located at (2,1), and Orange agent at (1,5). If a) radius=1 (left) Blue will move to (3,1) for 8 resources, while Red will either move to (1,4) or (2,5), both with 9 resources. If b) radius=2 (right) then the Blue will move to (4,3) or (2,3), while Orange will move to (2,3).*

2. **Collection** - All agents collect resources up to *maxEnergy* and the collected amount is removed from cell's *resources*. The order that the agents follow to collect is shuffled every time step.
3. **Cloning** - Agents whose *energy* equals *maxEnergy* produce offspring. The new agents have the same spatial location than their parents, and the *energy* of both (parent and offspring) is updated to *maxEnergy/2*.
4. **Energy expenditure** – Agents decrease their *energy* level by *energyCost*. If updated *energy* value is 0 or negative the agent dies and is removed from the simulation.
5. **Resource growth** – All cells increase its current *resource* value by *resourceGrowthRate* up to *maxEnergy*.

3.2 Equilibrium, equifinality, and multifinality

One of the most common approaches to the use of ABM as a virtual laboratory is the identification of equilibrium: scenarios where, after a given set of time, the state of the system does not change over time. This state can be defined in multiple ways, usually through the definition of summary statistics relevant to the modeler. In our case, we are interested on population dynamics so that the most reasonable summary statistic is the number of agents alive in a given time step. **Figure 3** shows an example of equilibrium: after an initialization time of 100 steps, the number of agents remains stable once the system has reached an upper threshold (i.e., carrying capacity). This value will remain stable even if we could be able to run the model for an infinite number of time steps.

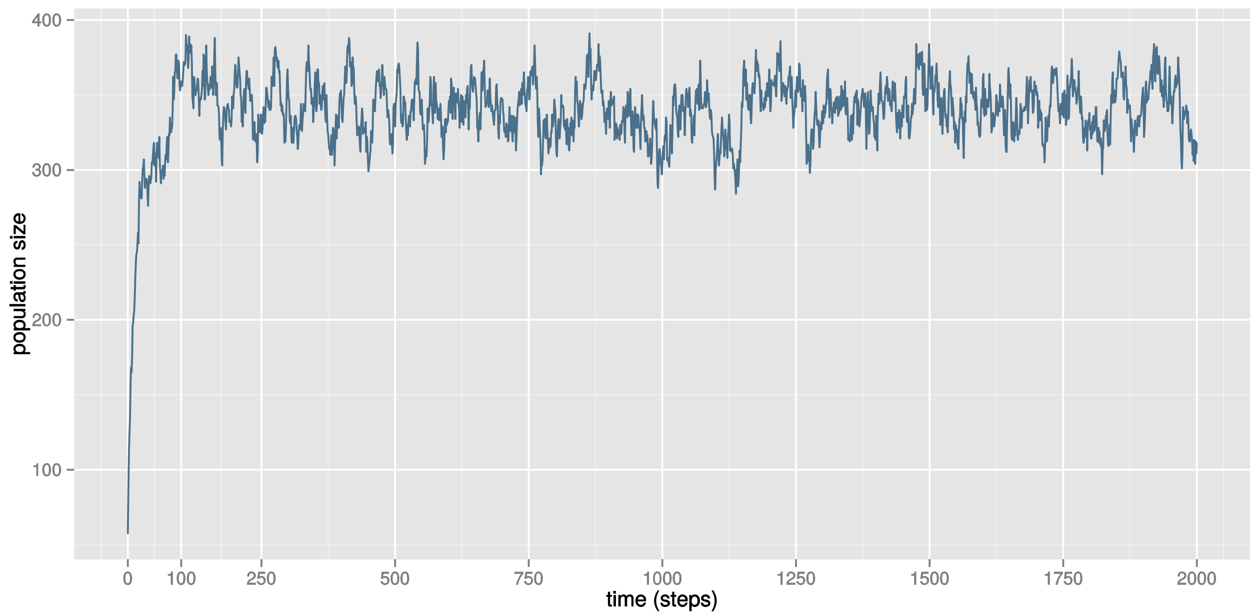

Figure 3 *Time series of population size for a single run of the model. After a initialization phase of 100 steps the system remains at equilibrium around a population of 340. Even though the value oscillates due to stochasticity the mean and standard deviation remains constant through from step 250 onwards.*

A related property of the system is equifinality: multiple scenarios can generate the same outcome. The consequences of equifinality for formal modeling has been thoroughly discussed in literature (Premo 2010, Crema et al 2014b). Even if the result of a computer model perfectly matches empirical evidence, one can never be sure that we identified the cause because alternate causes could potentially generate identical outcomes.

In addition, ABM often contains stochastic dynamics. In this case, the analysis of the system needs to take into account the emergence of multifinality. This is the opposite of equifinality, as it means that the same initial conditions can generate different trajectories and will never be identical even if they follow similar trajectories. **Figure 4** shows a simple example of both properties for the presented model. Multiple initial values for *nAgents* generate the same final outcome (i.e. population size), while identical initial conditions can develop into different trajectories.

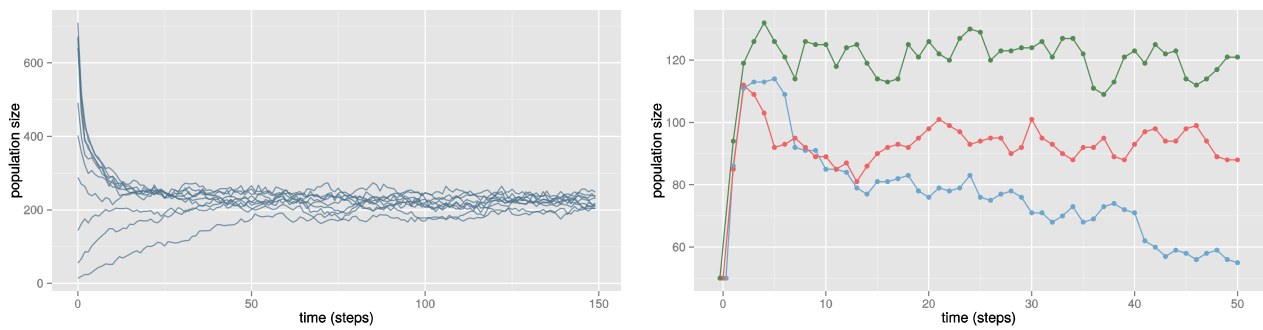

Figure 4 *Time series of population size portraying the effects of equifinality (left) and multifinality (right). In the first scenario 10 runs are initialized with different values for nAgents. After 150 time steps all of them remain at equilibria around the same population size of 220 and there is no way to know which nAgent value generated each final population size. In the second scenario 3 runs*

are initialized with the same value for the nAgent parameter (50). The same initial conditions generate completely different trajectories after 50 time steps.

3.3 Exploring the relationship between mobility and population size

We will use this basic model to explore how decision-making can generate the tragedy of the commons. In particular, does mobility (i.e., *radius*) influence the carrying capacity of the system?

We explored this relationship with the following experiment. For each value of *radius* between 1 and 30 we executed 1000 runs while fixing the rest of parameters (see **Table 1**). Each run was executed for 5000 time steps and we chose as the summary statistic the population size at the final time step.

Parameter Name	Description	Parameter Value
nAgents	Initial number of Agents	10
xDim	Coordinate range x	30
yDim	Coordinate range y	30
energyCost	Energy spent by an agent every time step	25
resourceGrowthRate	Resources increased in each cell every time step	25
maxEnergy	Maximum energy/resources any agent/cell can accumulate	100

Table 1 *Parameter configuration for the decision making model.*

Figure 5 shows the results of the experiment. A clear negative dependence between mobility and carrying capacity is detected despite the stochasticity of the model.

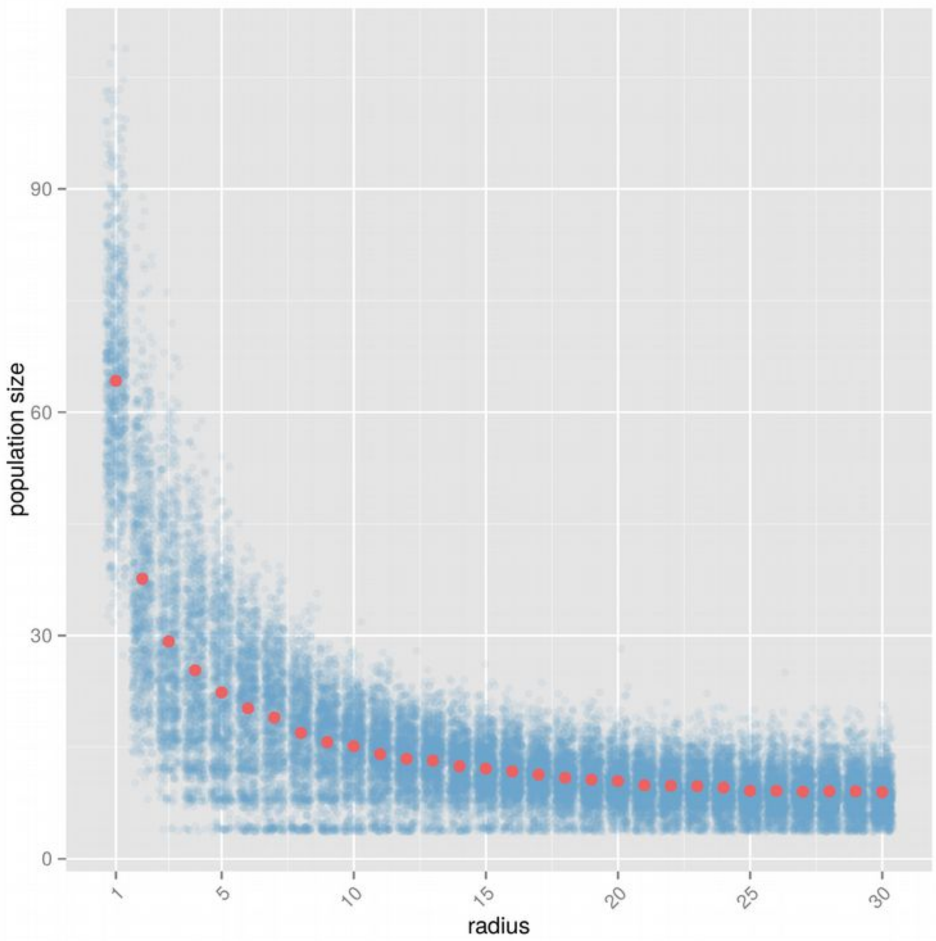

Figure 5 *Impact of radius (X axis) on population size (Y axis) after 5000 time steps. Each blue dot represents a run, while red dots illustrate the mean value for all the runs initialized with the same radius (from 1 to 30).*

The shape of this result suggests an exponential decay between the parameter *radius* and the final population size. The process is an example of the tragedy of the commons because the decision-making process of the agents do not take into account what other agents are doing. There is no cooperation, as the greedy algorithm looks for maximum individual benefit (i.e., the cell with highest *resources*). An increase in *radius* means that the agents are better informed at identifying the best locations on the grid. In the absence of cooperation mechanisms, imperfect information (i.e., low *radius* values) is the only way to escape the tragedy of the commons.

4 CULTURAL TRANSMISSION

Theoretical and empirical studies of cultural transmission have been associated with formal models for over three decades. Early seminal works (Cavalli-Sforza and Feldman 1981, Boyd and Richerson 1985) developed a foundation based on population biology, a theoretical framework that facilitated the development of an extensive corpus of equation-based models depicting different modes of cultural transmission.

More recently, the decreased cost and increased power of computer simulations is offering new options, enabling solutions to previously intractable equation-based models, and the potential to use alternative modeling framework such ABM simulations (Mesoudi and O'Brien 2008, Mesoudi and Lycet 2009, Powell et al 2009). These advances are easing the development of models tailored to specific anthropological and archaeological questions as well as the integration of aspects that are hardly tractable standard equation-based models. Stochastic elements other than cultural drift (i.e., the change in the frequency of cultural variants due to random sampling), such as payoff associated with different cultural variants (Lake and Crema 2012), or realistic fluctuations in the background selective environment (Whitehead and Richerson 2009), can now be easily incorporated. Similarly, early models have been expanded to explore the role played by space (Premo and Scholnick 2011, Bentley et al 2014).

These advances are not limited to theory-building, but are increasingly illustrating the possibility of improving our understanding of how to link empirically observed patterns to plausible generative processes. These include both simulations designed to test the analytical power of existing statistical analysis for cultural evolution (e.g., Eerkens et al 2005, Crema et al 2014a, Premo 2014), as well as attempts to test evolutionary hypothesis for specific historical contexts (e.g., Kandler and Shennan 2013, Acerbi and Bentley 2014, Crema et al 2014b, Barton et al 2011).

However, the most successful line of inquiry remains the theoretical exploration of different social-learning strategies. These can be broadly distinguished depending on whether the transmission is intra-generational (horizontal *transmission*) or inter-generational (*vertical* and *oblique transmission*). Additionally, the choice of a given variant can be dependent on its intrinsic quality (*content-biased transmission*), the properties of its bearer (*model-biased transmission*), or other contextual evidence such as preferences for more common or rarer traits (*conformist bias* and *anti-conformist bias*). Alternatively, the transmission can be *unbiased*, so that the probability of selecting a given variant is simply given by its relative frequency. Readers interested in this rich literature can refer to the review papers by Henrich and McElreath (2003), Laland (2004) and Mesoudi (2015) as well as book-length treatments of the subject by Richerson and Boyd (2005) and Mesoudi (2011).

Here, we illustrate how these theoretical models of social learning strategies can be expressed as an ABM, by exploring how different modes of transmission combined with different population sizes can affect cultural diversity (ODD document for the model available as **Appendix 2**).

4.1 Model Description

Consider a population of *nAgents* agents located in a bounded rectangular space that is *xDim* × *yDim*. Each agent is described by its spatial location (*x* and *y*) and cultural traits in an array composed by *nTraits* “slots” that can be one of the values defined by the vector *traitRange*. For example if *nTraits*=3 and *traitRange*={0,1,2,3,4}, an agent can have traits {0,2,0} while another one might have {0,1,1}. This array of numbers represent the cultural traits possessed by each agent following classical Axelrod's model (1997b). Thus in the example just given, the two agent share the same cultural trait (the number 0) in the first slot.

When the simulation is initialized, all agents possess random permutations of these traits, as well as a random spatial coordinate. The simulation then proceeds with a discrete number of time-steps, each where the following two processes update the location and the cultural traits of the agents:

1. *Movement*. All agents move to a random location within a euclidean distance *moveDistance*.
2. *Cultural Transmission*. All agents engage into one of the following modes of social learning:

a) *Vertical Transmission.* With probability *replacementRate* a random subset of *n* agents are selected and removed. Then *n* agents (i.e., the same number of agents being removed) are introduced in the model, each possessing the cultural traits and the spatial coordinates of a randomly selected agent from the previous time-step. However, with probability *innovationRate* some of these newly added agents will have a new value on one of its cultural traits slots.

b) *Unbiased Transmission.* Each focal agent first defines its social teacher as a randomly chosen agents located within distance *interactionRadius.* If a social teacher is found, the focal agent choses a random index value from its cultural trait slots, and copies the corresponding value of the social teacher. Thus, for example, if the focal agents have {3,2,0}, the social teacher {0,1,1}, and the random index value is 2, the updated cultural traits of the focal agent becomes {3,*1*,0}. With probability *innovationRate* the newly acquired is swapped with a random value from *traitRange.*

c) *Prestige-Biased Transmission.* As in the *unbiased transmission* model, the focal agents selects a social teacher within distance *interactionRadius.* This time, the probability of being selected as social teacher is however proportional to the trait value at the index number *prestigeIndex*. More specifically the probability of selecting a social teacher *x* is given by (prestige trait value of agent *x* + 1). Thus if three agents located within distance *interactionRadius*, have respectively 3, 2, and 0 as trait value at their *prestigeIndex*, the probability for the first agent to be selected is (3+1) / (3+1 + 2+1 + 0+1)= 0.5. As for the *unbiased* model, the actual cultural trait slot being copied is randomly selected, hence portraying social contexts where the learners selects a teacher based on its prestige, but it is not always aware of which cultural trait determines such prestige. As in the other models, with probability *innovationRate* the newly acquired is swapped with a random value from *traitRange.*

d) *Conformist Transmission.* The focal agent defines the pool of social teachers (i.e. all agents located within distance *interactionRadius*) and a randomly selected index value for its cultural trait slots. Then it copies the most common value amongst the social teachers (randomly selecting between the most common ones in case of a tie). With probability *innovationRate* the newly acquired is swapped with a random value from *traitRange.*

The four transmission modes are exemplified in **Figure 6**.

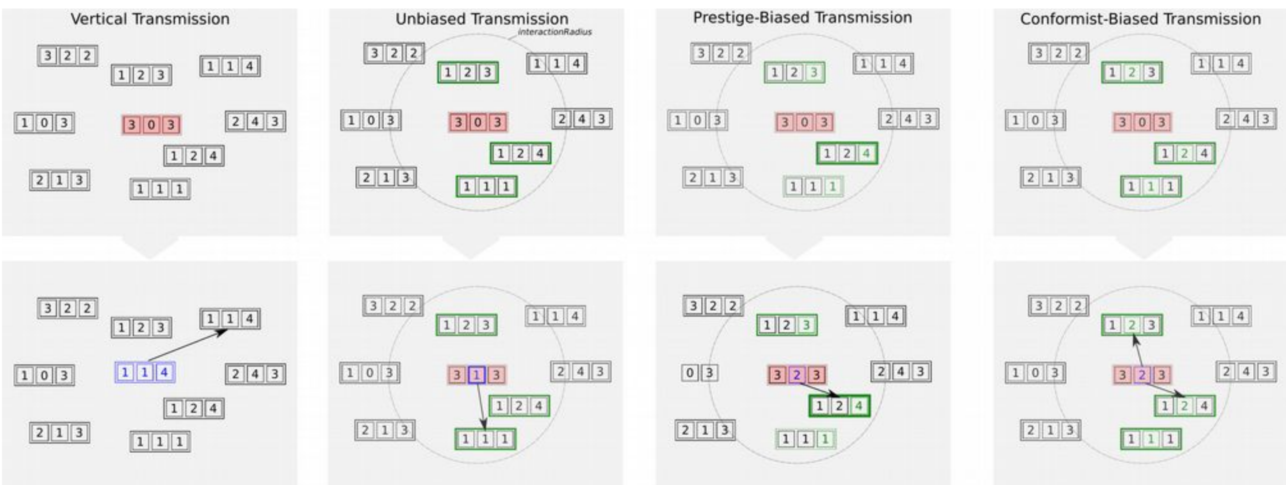

Figure 6 *The 4 implemented models of cultural transmission. Vertical: offspring copies the trait*

from parent, Unbiased: Unbiased: random copy of one trait from one neighbor; Prestige-biased: a random trait is copied from the neighbor with higher value of the third trait; Conformist biased: the most common trait between neighbor is copied.

4.2 Exploring the effects of population size and learning strategy on cultural diversity

One simple question we can explore with this model is how different modes of social learning are affected by population density. To do this, we explore a range of parameter values for *nAgents*, (the number of agents in the simulation), and record a summary statistic that explores some properties of the cultural traits possessed by the agents. One approach is to count the absolute frequencies of unique combinations of traits, and compute the Simpson's diversity index (Simpson 1949). This will be bounded between 0 (all agents possess the exact same combination of traits) and 1 (all agents are unique, i.e. no two agents have the same combination of traits). The simulation will help us constructing expectations for a variety of questions. With everything being equal do we expect to observe different levels of cultural diversity for different modes of cultural transmission? Does variation in population size affects the levels of cultural diversity? If so, do different learning strategies exhibit different relationship between population size and cultural diversity?

We explored the relationship between population size, learning strategy, and cultural diversity with the following experiments. For each of the four modes of cultural transmission we executed 1,000 simulations fixing all parameters (see **Table 2**), but randomly drawing a different value of *nAgents* from a uniform probability distribution bounded between 5 and 500.

Parameter Name	Description	Parameter Value
nAgents	Number of Agents	Random value between 5 and 500
xDim	Coordinate range x	10
yDim	Coordinate range y	10
replacementRate	Agent replacement rate (only used for *Vertical Transmission*)	0.1
moveDistance	Distance moved by each agent each time-step	1
interactionRadius	Sampling radius for cultural transmission (not used for *Vertical Transmission*)	1
innovationRate	Rate of innovation	0.01
nTraits	Number of slots containing cultural traits	3
nTraitRange	Range of possible cultural trait values	0,1,2,3,4
prestigeIndex	Index value for the prestige trait	1

Table 2 *Parameter configuration for the cultural transmission model.*

We ran each simulation for 1,000 time-steps, and recorded the Simpson's index in the final time-step. **Figure 7** shows the results of this experiment.

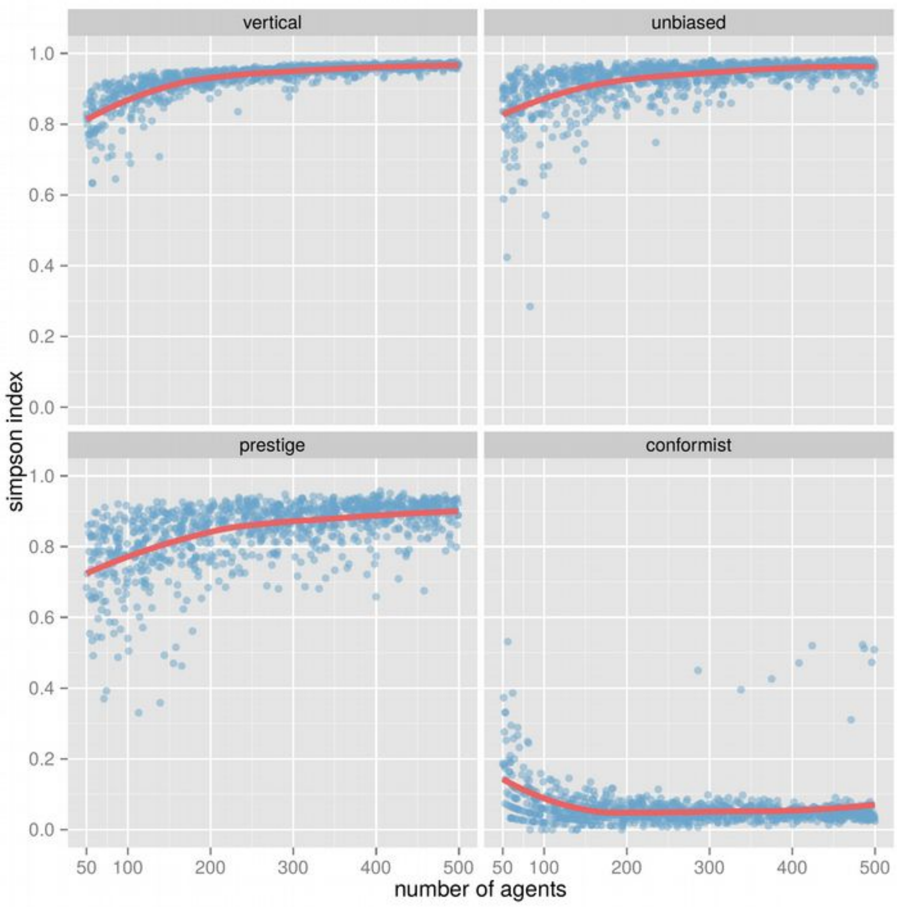

Figure 7 *Effect of transmission mode on Simpson's diversity index for different group size.*

The first thing we notice in all the plots is how the variance in the diversity index is reduced, although with a different magnitude, as a function of *nAgents.* This is not surprising, as with low population density the effects of sampling error have a greater impact in the change of relative frequencies (i.e., drift is a strong component in the system), so that diversity value is hardly stable and exhibit strong fluctuations. With higher population size the effect of drift is reduced. All models, except for conformist learning, exhibit an increase in diversity index as a function of *nAgents*, albeit the absolute values as well as the variance in the output is different between the three. For example, *Prestige-Biased Transmission* seem to show larger variance and slightly lower diversity statistics. This is possibly determined by the fact that learning bias in this case reduces diversity, as agents with low prestige will copy high prestige individual, whilst high prestige individual will copy each other. This reduces the potential number of cultural traits that can be copied, funneling the system to a lower diversity compared to unbiased random encounters. In the c*onformist transmission,* this process becomes extreme, as agents learn simultaneously from multiple social teachers without any stochastic effect.

5 CONCLUDING REMARKS

This paper explores two models of social processes that are commonly found in small-scale societies, where decisions undertaken for resources and cultural transmission can have a major effect on societal/ecological dynamics and their evolution. By providing research-relevant models in this presentation, our intention is to provide useful models that can provide key lessons in exploring such societies as well as giving readers an opportunity to implement these models in common, open and free computational languages and modeling platforms. Common themes in ABM are demonstrated, showing how situations of population equilibrium could derive in cases where resources are consumed and generated at fixed rates. We see that knowledge by agents can have detrimental influence on agents, particularly in situations where there is no cooperation and agents have more knowledge of their environment. The paper explores issues of population density, where this, at times, has dramatic impact on how given societies could evolve and affect cultural transmission to future generations. Different methods of transmitting cultural understanding could lead to very different situations that lead to more or less diverse cultural traits.

Looking beyond the demonstrations provided in this paper, we see that ABM will continue to expand in its use to understand how complex, small-scale societies evolve over time. We already see that more powerful computational resources are being increasingly applied to study large-scale parameter spaces that represent varied and diverse sets of behaviors for these and other types of societies (Dubitzky et al. 2012). Finding commonalities between ancient and more modern small-scale societies is another important research theme where ABM can further assist, as theoretical underpinnings can be tested irrespective of time and place. At a general level, increasingly research focuses on how small-scale societies can affect ecosystems and if such impacts can lead to more or less sustainable social-ecological systems (Smith and M. Wishnie 2000). The methods and examples advanced here are intended to assist in such research endeavors by providing practical, research-focused models developed from a bottom-up perspective and in open and free formats.

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