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When All Agents Die: Analyzing the "Failures" in an Agent-Based Model of Human Foraging

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Abstract

When running a simulated social-historic scenario, we often find situations in which all agents die, even though the simulated population appears to grow in the first steps. Is this a signal that something is wrong in the computer model or its implementation? We analyze this issue in our computer model of cooperation and cultural diversity among hunter-gatherers in prehistory. We have calculated more than 11,000 possible parameter combinations, taking into account the growth and decay of the population and the availability of resources in the environment. When the initial population is too scarce or too big for the local availability of resources, it begins to decrease until it disappears. This can be a very trivial test for the Malthus condition, but we have discovered that there are other important correlations affecting social and economic factors that should be explored.

Keywords: agent-based models, hunter-gatherers, parameters test, social simulation

Introduction

In this paper, we discuss how models may be used to make inferences about the most remote past, when humans depended for subsistence on hunting and gathering. Our hypothesis begins as an extremely abstract model and adds degrees of behavioral sophistication, which influence the results. These influences are discussed in a step-wise fashion so that the reader can see how changes to the model's assumption influence outcomes.

Although the models being used in this paper are agent-based computer simulations, we describe the interaction of variables in the models using equations. To understand how this is translated into an agent-based model, the reader is referred to commented code published recently at the CoMSES Network-OpenABM

https://www.comses.net/codebases/f16c9d1c-8c90-42dd-9ef4-d2f5980ac8a8/releases/1.0.0/

Testing Different Scenarios

First Scenario: Simplest Foraging Behavior

We have implemented a series of computer models in which "virtual" hunter-gatherers survive on what they randomly find around them, with no technology for resource acquisition, with a catchment area constrained only by technical limitations in transport and mobility, and without any mechanism of social interaction allowing for cooperation: there is no transfer of food, technology or labor force. This scenario is typical for foraging behavior, where it is assumed agents should find, capture and consume food containing the most calories while expending the least amount of time possible in so doing (Del Castillo and Barceló 2012; Smith 1983; Stephen and Krebs 1986; Winterhalder and Smith 1981). If such an assumption were true, we would say that hunter-gatherer's survival would depend just on the availability of resources, and the nature of economic behavior would be merely adaptive. We take this simplified hypothesis, to explore some of their behavioral consequences.

In our virtual world, agents are not individuals but reproductive units (two adults and a number of descendants). The amount of labor available for hunting and gathering is based on the number of members the reproductive unit has; the agent survival threshold adjusts to the number and age of its members. The algorithm can be run with alternative survival threshold values but we offer here results for an assumed fixed average value of 2,000 calories per individual day (Cordain et al. 2000; Eaton, Eaton III, & Konner 1997; Hill et al. 1984; Leonard 2014; Pontzer 2015; O'Dea 2016; O'Keefe et al. 2010; Simmen et al. 2017; Ströhle et al. 2010; WHO 1991). One-time step (cycle or "tick") in the simulation roughly represents what and where an agent is able to do and move in six months, therefore at the agent level the threshold value is defined as 730 kilocalories multiplied by the number of labor units in this household.

Each time an agent ("family") cannot obtain energy up to the summed survival threshold of the entire family, it loses one of its members (labor unit), and the survival threshold and labor capacity is redefined for the remaining members of the household. In the same way, every 30 ticks (what roughly equals the average time a child needs to arrive to reproductive maturity), a new agent is born, and will live until the total acquired energy is below the survival threshold. There is additionally a stochastic mortality mechanism (death by accident or illness). When survival is possible and the number of members in an agent (expressed in labor units) is greater than a variable parameter, the current agent reproduces and gives birth to a new agent, who has with half the parent labor, the same technology, and the same identity. Our model clearly distinguishes from the more complex demographic engines to generate agents in hunter-gatherer scenarios (Olives et al. 2015; Olives et al. 2018; Smaldino et al. 2013; White 2014; White 2016). The purpose of this exercise is to discover the global dynamics of the simulated agent population, in terms of an increasing or a decreasing trend, and not to reproduce an existing ethnographically described population.

In the simulation, the environment is divided into equally sized patches. Agents move within an area defined by a variable radius, fixed at startup, and whose variations are explored building alternative scenarios. This radius depends on the transport technology available at each moment. Each patch of the virtual environment has a number of RESOURCES (r_i), measured in kilocalories (kcal). The availability and abundance of resources are assumed to vary normally through the landscape; therefore, we have used a Gaussian distribution of values. By modifying the mean, we explore different scenarios (a poor versus a rich world). The standard deviation of resources in the world has been fixed for all the simulations. The year cycle has two differentiated seasons, so that in the cold-dry season, the availability of resources is half of the availability of resources during the warm-humid season. Resources at each patch have also a DIFFICULTY level (h_i). It is also a normally distributed parameter counting the difficultness of resource acquisition.

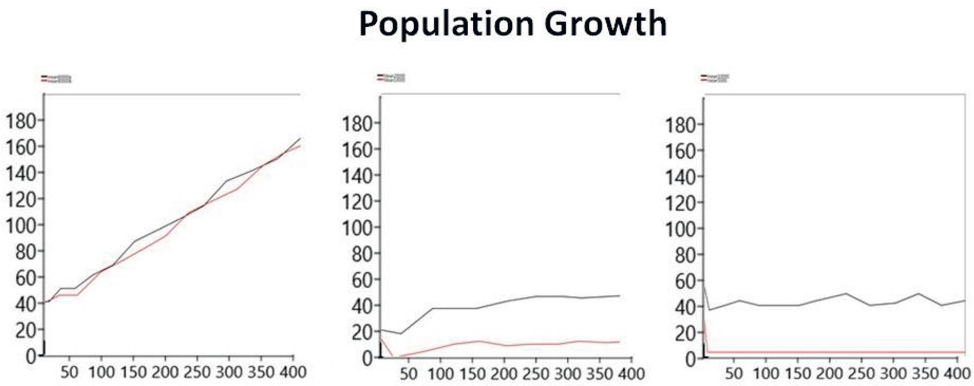
Social agents survive only if they have success in acquiring energy available in the environment by means of hunting and gathering. It is modeled in terms of a simple energy transfer from the environment to the agent up to the limit defined by the survival threshold (Garfinkel et al. 2010; Iwamura et al. 2014; Young and Bettinger 1992). In our case, the energy each agent acquires is:

$$E_i = R_j f_{i(t)} - Surv_i$$

Equation 1

The agent takes from the environment what it can extract according to the amount of labor it has. This appears as the factor ($f_{i(t)}$) in the equation, the acquired proportion that the agent has effectively obtained by means of its labor and technology, which is multiplied to the amount of resources existing in the actual patch (R_j) in kilocalories. Given that we assume in the simplest scenario there is no storing capacity, what the agent takes from the environment is just what it needs at current time - the survival threshold ($Surv_i$).

A specificity of our model is that agents do not just extract resources from the environment, but there is also an additional factor of difficulty affecting the probability of survival (Equation 1). The transfer of energy from the patch to the agent is mediated by the difficulty of access, and how labor+technology



Increasing Population of sedentary individuals in the richest world scenarios. (Two scenarios with a mean of 8000 kcal at the warm season and 4000 kcal at the cold one).

Stable Population of sedentary individuals in medium riche world scenarios. (Two scenarios with a mean of 10000 kcal at the cold on; another scenario with a mean of 5000 kcal at the cold one).

Stable Population of sedentary individuals in relatively poor world scenarios. (One scenario with a mean of 5000 kcal at the cold onde; one scenario with a mean of 2500 kcal at the cold one).

Figure 1. Results of the first scenario foraging behavior and with an in increasing resource irregularity fixed for a standard deviation = 1000 kcal.

allows acquiring a percentage of energy. The proportion of the total resources at the patch extracted by the agent is then:

$$f_{i(t)} = \frac{1}{1 + \frac{1}{hi(t) \times li(t)^{\beta i(t)}}}$$

Equation 2

In other words, agents get the quantity of kilocalories they need from the patch they are situated, provided they have enough labor to compensate for the difficulty of resource acquisition. As already defined in case of Equation 1, fi(t) measures the proportion of existing resources at the actual location the agent can obtain. It depends on the quantity of labor available at this time step (li (t)), the efficiency of the technology at hand (βi(t)), and the local difficulty (hi(t)) of obtaining the resources existing at that place, harder to obtain in the cold season than in the warm one. The maximum value for fi(t) is 1, indicating the amount of work available and the effectiveness that current technology (βi) contributes to compensate for the difficulty of accessing resources. When the value of fi(t) is less than 1 but greater than 0, we can deduce that the working capacity and technology available only allow obtaining a proportion of the available resources.

A rich world scenario would be that in which there are plenty of food and resources available, and the reduction of resources during the cold season has no effect on survival. We have modeled different hypothetical "rich world scenarios," on the assumption that the mean of resources in the environment at the worst season exceeds many times the survival threshold of virtual families. In our model resources diminish at odd cycles ("cold" season) and they recover the initial value at even cycles ("warm" season).

We have implemented the model in such a way that at odd cycles, when resources do not regenerate naturally, the amount of resources available in each cell should be equal to the half of what existed at the warm season minus what the agent extracted at the previous time-step. Therefore, a gathered patch will still be worse than an unharvested patch even after the shift to the cold season. At the next cycle, resources on each cell are re-initialized to the value they had at the last warm season. Obviously, in rich enough worlds, seasonality does not have any impact, but when the mean of resources in the cold season is below survival threshold, survival is at risk.

Initial, exploratory work suggests that "rich" environments appear when resources during the warm season are above 13 times the survival threshold.

It is not a surprise that in these conditions, most

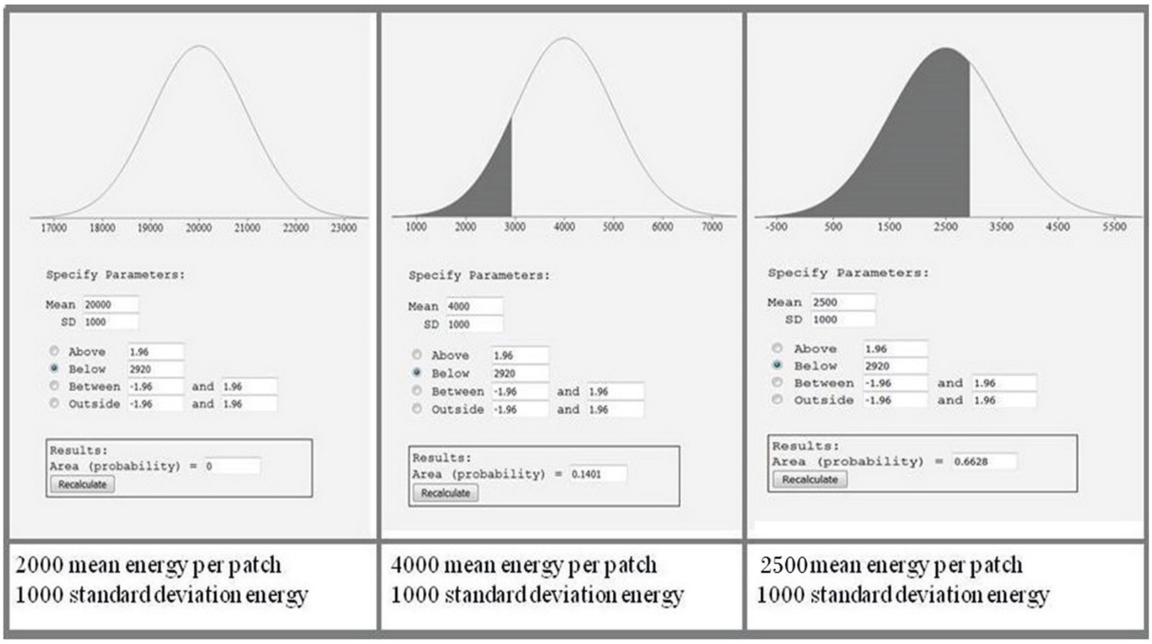


Figure 2. The results show the probabilities of finding enough resources for survival in three different scenarios of resource availability for an example with 4 labor units.

agents live and population grows if there is enough food for everyone (Figure 1). Even in the case of sedentary agents (radius of movement fixed to 0), a population will survive or even increase, provided there are resources well ahead of the survival thresholds. This is the classic Malthus hypothesis. Our results are consistent with modern work on Malthusian growth computer simulations (Lanz et al. 2017; Peretto and Valente 2015).

Given that the amount of resources has been simulated in terms of a Gaussian variable with a fixed standard deviation, and agents have been initialized on random patches at start-up, it becomes easy to calculate the probability of finding enough resources for survival using normal probabilities. In the rich scenario with a mean of 20,000 kcal of energy in the environment at the warm season (and a uniform irregularity estimated in terms of a sd = 1000), there will be 0 probability to find some area with a quantity of resources below the survival threshold. In "poorer scenarios", the probability of being on a patch where survival is not possible will be higher (Figure 2). The prior probability of survival can be computed from the probability of availability of enough resources (Barceló et al. 2014). In the case of mobile agents, such prior probability changes every time the agent takes the decision to move.

Second Scenario: Mobility Decisions

We have introduced a mobility mechanism to increase the probability of survival when an agent does not find enough resources locally: move-to-another-place. This has been implemented as a mobility decision (Figure 3). Two options are open for selection:

1. Stay at place
2. Move to another place

At first, the agent evaluates its chances of surviving in the next season. The expected quantity of resources at next cycle is calculated by the agent on the basis of its knowledge of the current season and the nature of the next season, and on the amount of energy it has already taken from environment at the present cycle. Consequently, if

$$\textit{Expected}\ R_{i\,(t+1)} - e_{i\,(t)} > \textit{Expected}\ \text{survival-threshold}_{(t+1)}$$

Equation 3

on the next time-step, the agent remains at the patch and does not move. Otherwise, it moves randomly to any other unoccupied patch in a fixed neighbor-

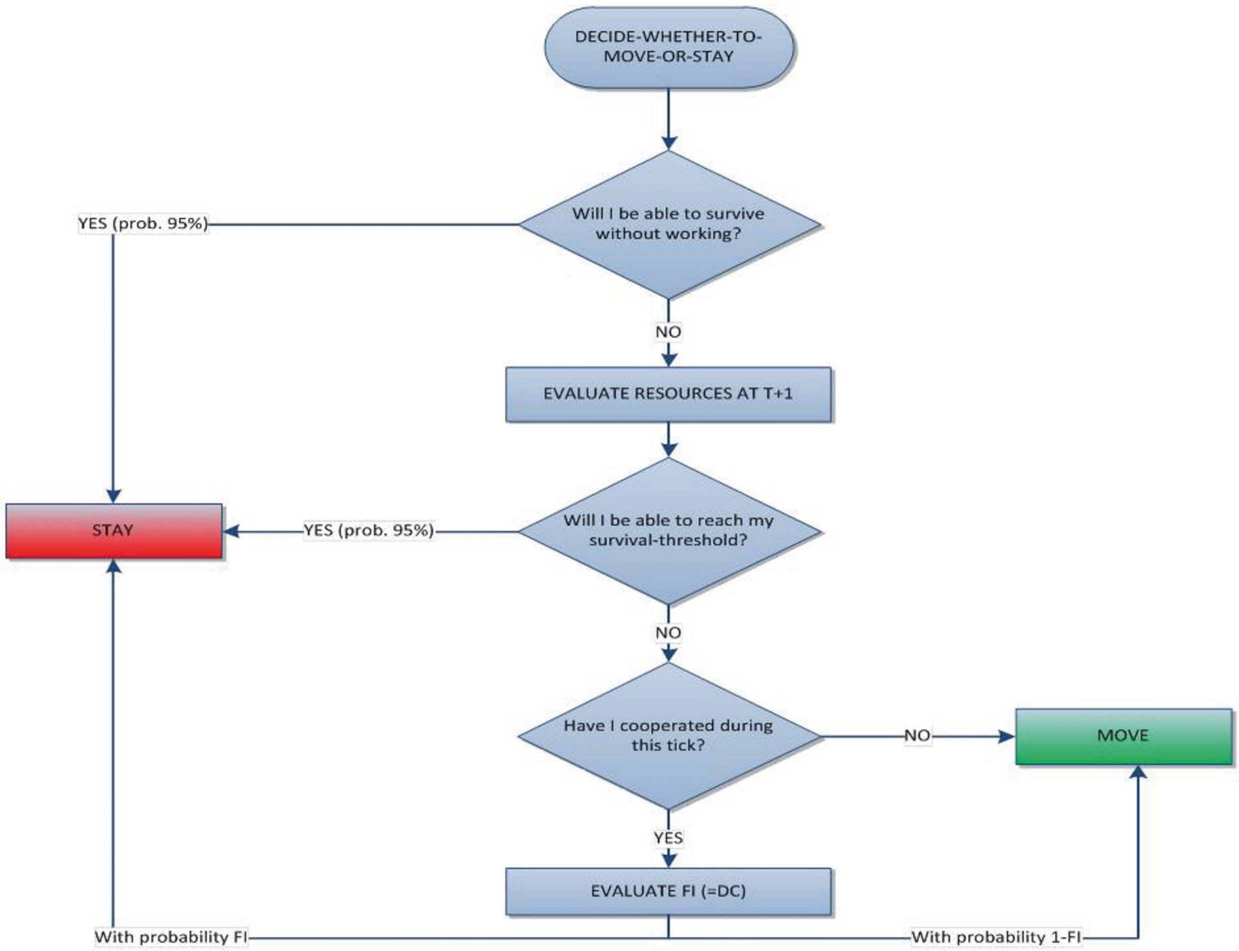


Figure 3. Functional diagram of the model showing agents decisions process.

hood, limited by available technology for transport and movement. This dynamic is very loosely based on the marginal value considerations from classical optimal foraging theory (Gurven et al. 2006; Keeley 1988; Keene 1979; Konner and Eaton 2010), although in a very simplified way.

Obviously, prehistoric hunter-gatherers nor hunter-gatherer bands known in historical times hardly ever displaced randomly and hunted-gathered at any place within a constrained neighborhood (Grove 2009; Perreault and Brantingham 2011). Displacement among hunter-gatherers can take many different and varied forms:

- the displacement of all the population or a part of it,
- wandering randomly through the lowest cost-surface until finding the richest place, or the place where enough resources are most accessible, or
- going directly using the most direct and fastest way to the place where there is a memory of plenty of resources.

Because the condition is to move to an empty patch, there is not any chance that two agents coincide at the same patch. In any case, we have added a small amount of random noise (a randomly selected 0.05 % of agents always move). We have considered that a small amount of system stochasticity is necessary to avoid the risk of local minima. Exhaustive testing of simulations with and without such amount of random noise suggests the advantages of this approach.

If the next season is a warm one, even the proportion of resources the agent has extracted in the previous season will be naturally reproduced, and

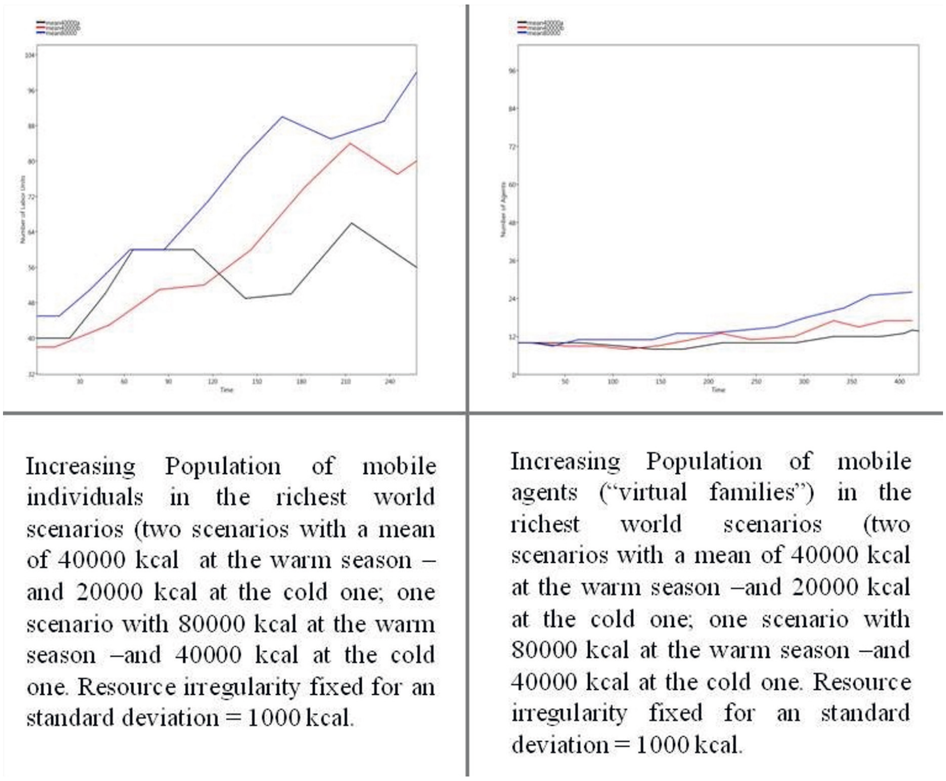


Figure 4. Survival comparative charts explains how introducing mobility in a rich world (when the availability of resources in the cold season exceeds seven times the survival threshold), does not affect survival, and hence population grows.

survival will be possible. In case the next time step is a cold season, local resources will reduce drastically, and moving to another place will be imperative.

Exploratory work on different scenarios suggests that when the availability of resources in the cold season exceeds seven times the survival threshold, introducing mobility does not affect survival. Consequently, population grows, both at the level of the number family members and the number of families in the territory, although the growth of families increases at a much slower scale (Figure 4).

The reason for the differences in the rate of growth lies in the social nature of reproduction. Within a family, the number of members increases geometrically linearly related to the availability of resources, whereas within a landscape, the number of families increase arithmetically depending on the internal growth of family members. The simulation reproduction engine generates a new family when the previous family's labor units grow to greater than or equal to a specified size threshold of 10. Other values are possible, and their effect on hunter-gatherer survival should be explored (Lesthaeghe 1998; Rijpma and Carmichael 2016; Skinner 1997). We think that this threshold for family "leave and cleave" is fixed in most societies through social norms. In this paper, and to reduce the parametric space, we have fixed it for the examples in this paper, using average family sizes from ethnological work in Patagonia (Barceló et al. 2015a). We have just added 5 % of random noise to account for accidental variability.

To our surprise, when introducing small amounts of random mobility (up to a 2 % of the landscape) in most cases, even in relatively rich worlds, all agents die, when in the sedentary scenario survival was guaranteed (Figure 5). The rate of decreasing population is logically related with the mean of resources, and it is independent of the radius of mobility.

Starvation and population extinction only happen when the prior probability of survival in the cold season is below 55 %, based on the number of patches where resources are above the survival threshold for a virtual family of 4 members in average. However, it is relevant that even at higher, prior probabilities; population diminishes, when in the same circumstances, sedentary populations grow. In any case, the key factor is still the availability, irregularity, and accessibility of resources. The amount of mobility has no impact on the rate of mortality. We have simulated scenarios where agents are allowed to move in the immediate 2 % of the total environment looking for enough resources, in the immediate 12.5 %, 50%, and even at the entire territory. In the absence of any

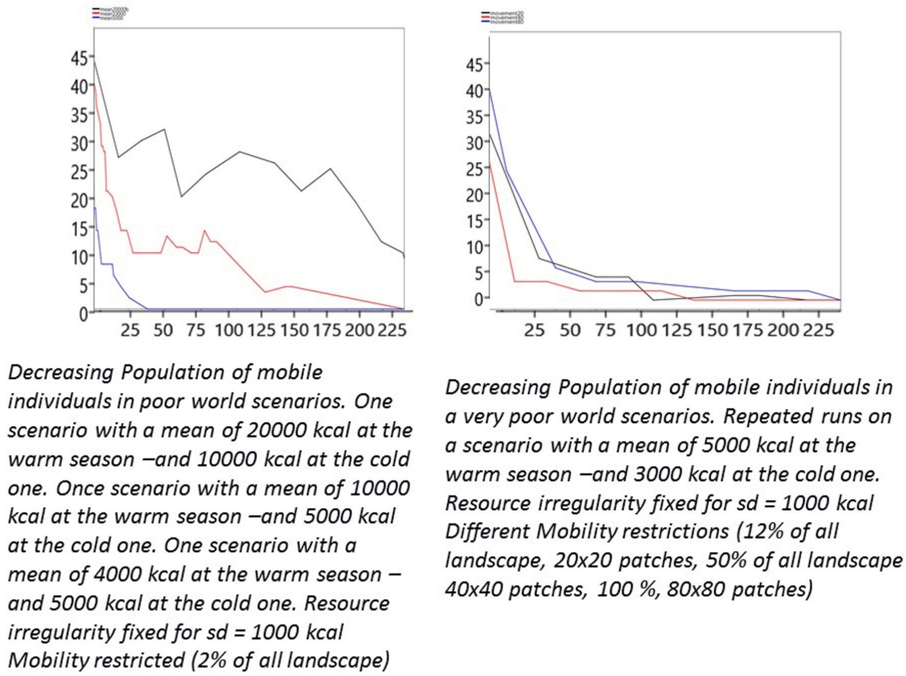


Figure 5. Comparative charts showing the variation in the conditions of survival introducing small amounts of mobility.

other factor, mobility in itself cannot increase the probability of survival.

In our results we see that when resources diminish, families decrease their number of members, and hence the amount of labor available to compensate for the local difficulty of accessing existing resources. If the simulation started with families of four members (where the number of members is a Poisson distributed parameter with small values of lambda, that is, with very small variability), the mean number of labor units per family rapidly converges to two. In such conditions, although the survival threshold also diminishes, the probability of acquiring enough resources is affected by the local difficulty.

Mobility increases stochasticity in all simulated scenarios. That is, at each run of the same scenario (with the same values and the same parameters at start-up), the evolution of the population differs. This is a consequence of the increasing irregularity in agents' revenues. The mean energy acquired by labor unit is fairly constant in all simulated scenarios, but when adding mobility, its standard deviation also increases, varying enormously from one cycle to the next. That means that although most agents behave in the same way trying to extract the maximum amount of energy they can find locally; the local availability varies. We have fixed such an irregularity assuming a Gaussian distribution with a standard distribution of 1000 kcal. This value should be interpreted as a very small irregularity in the richest world (12.5 % of variation) and increasing irregularity as the mean of resources is lower, arriving to 40 % of variation in the poorest scenario).

Third Scenario: Introducing Technology

The use of technology for increasing revenues is the main characteristic of human beings for at least the last 3.3 million years. We have studied the probable effects of technology –see parameter β in equation 2- in medium rich worlds (where the amount of resources in the environment at the worst season exceeds two times what a family of 4 members needs for survival). We explore technology effect as an exponent rather than a multiplied factor because of its implicit non-linearity compared with the influence of the labor force (Hekkert et al. 2007; Kremer 1993; Ruttan 1996; Solé et al. 2013).

In medium rich scenarios, the effects of technology on population growth of sedentary agents are small but relevant (Figure 6). Much more evident are its effects on mobile populations. If survival is at risk when opting for mobility even in a medium rich scenario, technology multiplies the effects of labor on the accessibility of resources and the probabilities for survival, and it reverts population decrease.

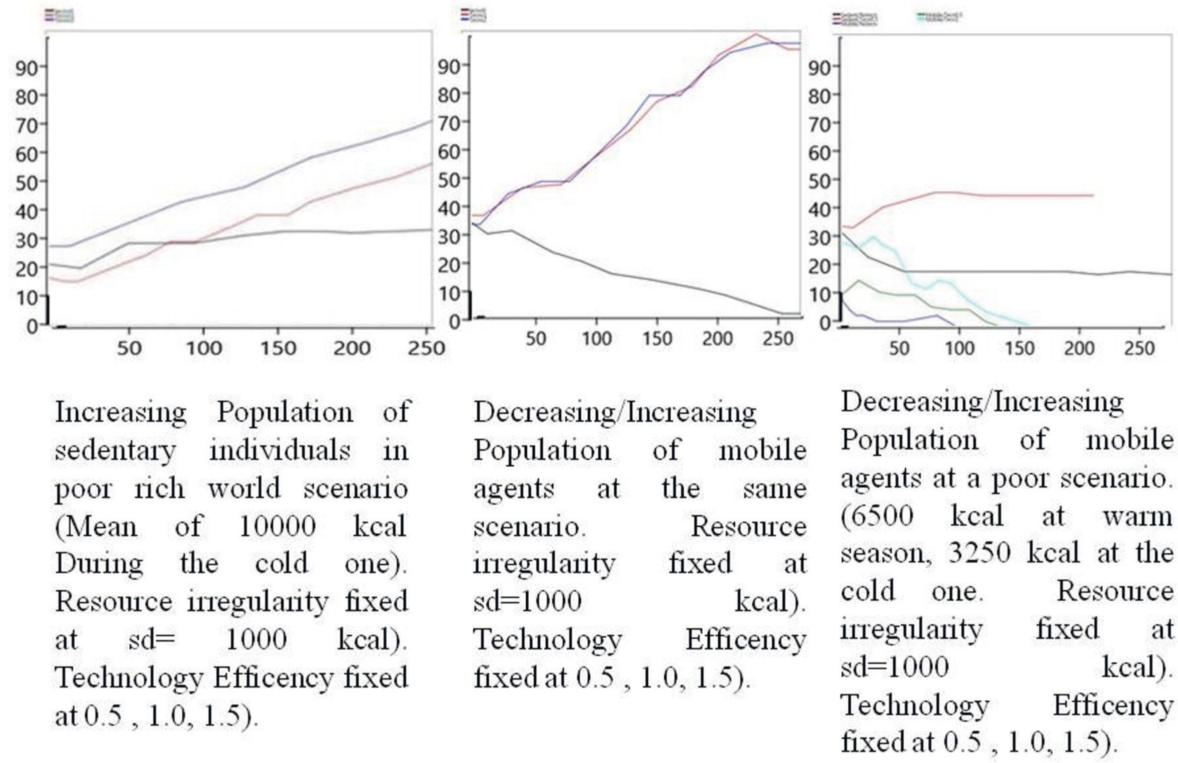


Figure 6. The advantages of technology related with three different scenarios of sedentary/mobile/resources abundance.

At poorer environmental conditions, technology by itself cannot revert the effects of mobility, stochastically increasing movements to low value cells, and as a result, most agents die in relatively short periods of time.

Fourth Scenario: The Effects of Cooperation ("Collective Hunting")

In our model, cooperation in a hunting-gathering band does not imply the transfer of subsistence, because what an agent acquires is limited to its current needs. Consequently, there is no surplus of food to be transferred, but there is always a surplus of labor not used when resources are rich enough and easily accessible with the current labor capability. This surplus of labor can be used in an abstract form of "collective hunting" (Hill 2002; Packer and Ruttan 1988). In our case, higher values of difficulty (h_i) are compensated by adding labor units from different agents in adjacent patches. In so doing, we understand "collective hunting" in the way it has been used in robotic simulation: each agent makes its own decisions based on its ambient circumstance, and the cooperation may emerge through local interactions among the robots, which is beneficial to the task (Cao et al. 2006).

In the simulation, agent i receives cooperation in form of labor (additional labor units) from agents that have labor in excess for their own survival, only in the case it is unable to reach its individual survival threshold on its own, and there is an agent with an excess of energy in the vicinity. If the amount of energy and the level of productivity is enough, the agent will act individually and collect as much energy as it needs.

There is no compensation for the excess of labor exchanged or calculation of differential costs. That is to say, there is no obligation to "return the favor." There is a constraint in the quantity of labor a "rich" agent can transmit to an agent "in need". Each agent has a "FREE-LABOR" attribute expressing the number of labor units the agent can lend to another without compromising its own survival.

The number of labor units a family needs to reach her survival threshold is:

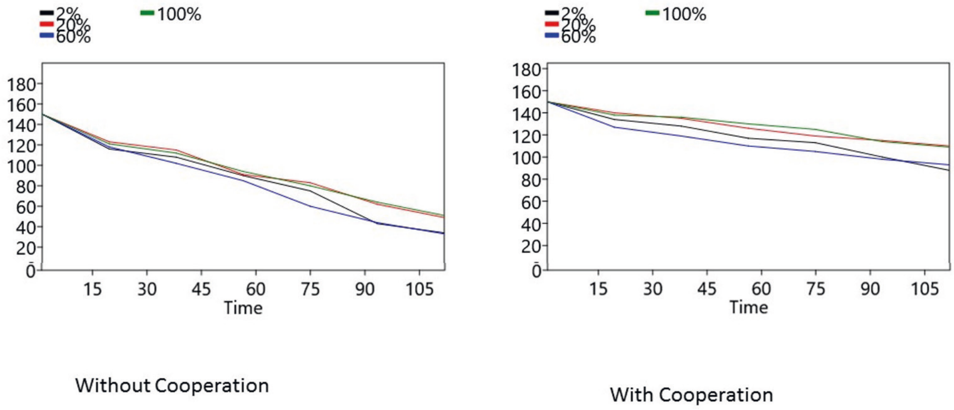


Figure 7. Decreasing population of mobile non-cooperative/cooperative individuals in a poor world scenario (one scenario with a mean of 6500 kcal at the warm season and 3250 kcal at the cold one. Resource irregularity fixed for and standard deviation = 1000 kcal.

$$Surv_i = \left[\frac{\bar{e}_i}{h_{i(r_i - \bar{e}_i)}}\right]^{1/\beta_i} - l_i$$

Equation 4

where $\bar{e}_i$ and $\bar{e}_l$ represents the acquired energy at the current tick (see Equation 1), l_i the actual quantity of labor, β_i the actual technology to compensate for the local difficulty (h_i) of obtaining the resources existing at that place, and r_i the amount of resources existing in the actual patch. The first term is the additional number of labor units the family needs to reach its survival threshold; and the second term, l_i, is the actual number of labor units the family has. This equation is the result of clearing $Surv_i$ in Equation 1 and adding relationships expressed in Equation 2 to calculate $\bar{e}_i$.

If the first term is greater than the second term, it means that the family does not have enough labor units to reach her survival threshold. Therefore, the value of $Surv_i$ (Equation 4) will be greater than zero (and thus FREE-LABOR = 0). In those cases where both terms are equal, the number of necessary labor units will coincide with the number of labor units the family has. Consequently, the value of ST will be zero (and FREE-LABOR = 0). However, if the second term is greater than the first term, it means that this family has plenty of labor units to reach its survival threshold (and thus ST = 0). The result of the subtraction will be negative (the family has extra labor units). The value of this subtraction (with changed sign) is precisely the amount of free-labor the family will lend another family in need.

With this supplementary labor, the system calculates the aggregated productivity $[\Delta f_{i(t)}]$ of an agent member of a group $G_{i(t)}$:

$$\Delta f_i\ (t) = \frac{1}{1 + \frac{1}{\left[h_i\,(t).\ (\sum j \in G_i(t) l_j\,(t)^{\delta\beta j(t)})^{\theta_i\,(t)}\right]}}$$

Equation 5

where $G_i(t)$ is the total amount of labor the group of agents that cooperate with agent i and $\delta\beta_i(t)$ the maximum technology within the group. There is an additional parameter modifying the total effect of aggregated labor at the social aggregate[1] ($\theta_i(t)$), capturing the idea that cooperation is less needed when there are plenty of resources. Productivity after cooperation is assumed to depend on labor productivity $p_i(t)$ in such a way that the higher the productivity the lower the expected returns of cooperation. Given a parameter

$$0<x_i<1$$

$$\theta_i\,(t) = 2 - (x_i)^{\alpha}$$

Equation 6

where α is a free parameter, so that 0 <= α <= 2. Therefore, θ_i is between 2 (when that particular patch

1 We expect that social cooperation will be less likely with distance. Instead of including a separated parameter for distance, we restrict calculations to the neighborhood group, which is defined as a list of agents within the neighborhood radius with similar "culture." Details of the "cultural" algorithm cannot be given here. The reader is referred to Barceló et al. 2014, 2015a.

is very poor in resources, $x_i = 0$), and 1 (when that particular patch is very rich in resources, $x_i = 1$). In general, we have calculated

$$xi = \frac{r_i}{mean\_resources\_on\_patches + (3 \times standard\_deviation\_resources\_on\_patches)}$$

Equation 7

Such an assumption produces a probability around 0.001 that x_i be greater than 1. In any case, if the result of the above equation is below 0 or above 1, x_i is reset to 0 and 1 respectively.

Preliminary results show that when fixing free parameters at medium/low values (Population = 150, Average technology = 1.05, Diversity = 0.1, labor average = 5, average storing factor = 0, internal change = 0.01) in a typical "poor resources" scenarios (mean resources on warm season patch = 6500 kcal), the advantages of cooperation are clear. Probabilities for survival increase in 53 % on average, although cooperation by itself is no guaranty of survival (Figure 7).

In any case, the size of the area where hunter-gatherers look for possible cooperants has no relevant effect on the advantages of cooperation. This result is unexpected. Cooperation apparently should depend on the distance over which social interaction can be defined. According to our preliminary results, the amount of cooperation is not inversely proportional to the distance between agents, defined in terms of the size of area where cooperants can be found. In our simulations, we have not measured any significant impact of interaction radius, given that the decrease of population is fairly similar when interaction is limited to the 2 % of the total area, when maximum allowed distance is fairly large (the agent can explore 60 % or even 100 % of the environment to look for prospective cooperants). In any case, this result cannot be used to deny the fact that ask-for-help diminishes with distance. The scenario we have explored here has a low population density (150 agents occupy just 5 % of available space). If population declines because of the poor resource scenario, there is less opportunity for helpers as well and so the population cannot recover. This fact creates isolated groupings of families that cooperate only amongst each other.

This result also shows the increasing stochasticity of human survival in conditions where cooperation is necessary. Cooperation may contribute to survival, but if agents rely on help from neighbors to make decisions, the final result is affected by uncertainty. Only when the technology for movement – transportation – allows an agent to contact with any neighbor in any place, then there is a clear increase in the chances of survival. However, when there are barriers to cooperation, either by physical distance or social distance (cultural identity), the advantages of cooperation are hardly evident.

Conclusions and Further Work

In this paper we have explored the old Malthusian view on population decreasing exponentially when resources are below a survival threshold. In our model, survival is not only affected by the raw quantity of existing resources, but by the "difficulty" of acquiring what is needed to survive. That means the more mobile the resource and the more difficult its spatial accessibility, the higher the difficulty, and therefore the more labor is needed to obtain resources up to the survival threshold, and more time is needed for the task. When more labor is needed, survival is less probable because the survival threshold increases given the higher quantity of people to be fed. In this scenario, any mechanism to increase the efficiency of labor has relevant effects.

When resources are low, not only because of their scarcity but because they are hard to obtain, hunter-gatherer survival is at risk because the amount of labor available to compensate for the local difficulty of accessing existing resources diminishes. When introducing small amounts of random mobility (up to 2 % of the landscape) in most cases, even in relatively rich worlds, all agents die, when in the sedentary scenario the chances of survival were higher. Our simulations show that random mobility is only a partial solution to compensate for the high difficulty and relatively low volume of resources at place.

In this paper we have just explored the consequences of random mobility. It is no adaptive decision, and it implies no rationality nor optimality criteria. Obviously, we need to implement a different mechanism that may include the selection of a better cell, using the calculation of prior probabilities for survival, and also considering the possibility of "memory." This would allow the agent to move towards the cell the agent remembers was a "good" one if it is not "far away" from the actual position. In any case, it is interesting to observe that even in the case of random movement agents do not bounce along until they settle on a good patch where they survive and grow. This is a consequence of seasonal variation in resources and the impossibility to survive at the current site in the cold season, once a majority of resources has already been harvested, and the remaining energy is well below survival threshold. An efficient technology for storing energy would be needed.

We have considered the effects of technology and social cooperation on survival in the simplest imaginable scenario. We have fixed low values of technology just to test the effects of social cooperation in the worst circumstances imaginable. We have tested the effects of collective hunting on survival in a scenario of very poor resources, where a population of agents has low chances of survival. If cooperation is not particularly beneficial in the case of rich scenarios, where resources are easily accessible, collective hunting does increase the chances of surviving in the case of low-density, decreasing populations.

Our results show that the advantages of cooperation are clear (probabilities for survival increase in 53 % of the scenarios on average), although cooperation by itself is no guaranty of survival. We have also shown that the radius of mobility, determined by the level of transportation technology, does not affect the advantages of cooperation. Increased chances for survival are as high in the case of using horses to travel through the entire landscape on a single cycle, as in the case of travelling on foot over a restricted 2 % of the area. In general, our results match those by Dyble et al. (2016), insisting on cooperation and sharing as concentrated within small clusters of households. These clusters represent one part of a multilevel social structure, and allow access to important cooperative relationships.

The effects of collective hunting as a form of cooperation have been studied by Skyrms (2004) and subsequent work (Antonioni, Tomassini & Buesser 2014; Gold 2012; Perc 2011; Pereira and Santos 2012; Skyrms 2008; Tomasello et al. 2012), and our results coincide with what would be expected according to this theoretical framework. Other important work that takes into account the effects of cooperation in the success of hunting is Janssen and Hill (2014 and 2016). All these works show the relevance of going beyond traditional views of prehistoric hunter-gatherers in terms of animal foraging behavior maximizing their net energy intake per unit time. Following Mithen (1988), we can say that while optimal foraging theory has been of considerable value for understanding hunter-gatherer subsistence patterns, there is a need for a complementary approach to human foraging behavior which focuses on decision-making processes and social cooperation.

Hunting in the past seems to have been a much more complex activity than expected, whose success, and hence the posterior probabilities of survival, are less deterministically affected by the availability of animals in the area or the efficiency of available technology. We need to incorporate social dynamics well beyond the standard animal foraging model: animals rarely cooperate, but cooperation is what made us humans. If a social agent cooperates with another agent, the chances of hunting success are higher, even in the case of low animal availability, or the difficulty in capturing them with available technology. Here, there is a social decision ("to hunt together or to hunt individually") that form the basis of Skyrms (2004) suggestion. According to this approach, we have modeled a cooperation mechanism in which an agent will cooperate with another:

1. when someone in the appropriate neighborhood will ask for help given its inability to survive using its own means. This neighborhood is constrained by the technology for mobility (MOVEMENT is a global parameter);

2. there is enough cultural similarity among both agents (the survival threshold needed to define the possibility of labor exchange is defined according the local circumstances);

3. the helping agent has labor in excess, and it can only contribute with what it does not need for its own survival;

4. only one agent can be helped at each time. The procedure is implemented so that all possible FREE-LABOR is given to the first agent asking for help. The remaining FREE-LABOR is invested in surplus (additional energy) when the current value of the STORING FACTOR is set > than 0.

Our results show that when following these constraints, cooperation increases the chances of survival, but in poor scenarios cannot avoid the outcome of the entire population starving.

We are conscious that connections to archaeology are only left implicit in this paper. For the moment, our aim has been to create a theoretical model of the possibilities of survival in prehistory, when technology was poorly efficient, and it hardly contributed to survival. There is a theoretical impossibility in obtaining empirical data to test the expectations that prehistoric people had about the advantages of mobility, the effects of available technology and the risk minimizing factor that comes from the possibility of increasing labor force cooperating with neighboring groups. We have intended to have some formal validation; that is, a test that the hypothesis may be true *within an artificial* (although objective) formal system (Barceló and Del Castillo 2016, Fforde 2017; Hasan and Tahar 2015; Yanow and Schwartz-Shea 2015), providing a reference background against which we can explain variability. The past cannot be reconstructed from archaeological data alone, because a given dataset contains insufficient regularities for predictive theorizing. Our computer model is just a hypothesis about *the more probable* behavior given some well-defined, prior assumptions, and it adopts the form of a deductive statement, whose foundation is merely formal. The model has been parameterized using ethnographic analogies and results of previous archaeological experiments (Barceló et al. 2015b). In any case, the model can be easily enhanced by introducing some archaeological corollaries of agent behavior, like the production of garbage as a sub-product of hunting and gathering, the material remains of residential places or burials signaling the number of deaths. A quantification of those elements would allow a partial empirical testing of the hypothetical model (Conte and Paolucci 2014; Geller 2014; Lee et al. 2015; Windrum, Fagiolo & Moneta 2007).

In the social sciences, models are often presented uncritically as faithful representations of reality. In this paper, we make no such claim. We argue instead that our models of hunter-gatherer survival are useful as devices for interrogating some prior hypotheses about human behavior in Paleolithic times. Does it mean that the model is wrong? Not necessarily (Epstein 2008). We have not yet explored alternative and more complex scenarios, because we were interested in simulating the simplest scenario to evaluate the effects of social cooperation and the transfer of labor force in the worst imaginable conditions. In any case, even this most simplified and abstract model suggests the enormous variation of effects a single decision or strategy had, and it contributes to understand the basis of randomness in human action, especially at times where social organization was dependent on local resources and the local configuration of those resources.

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References

Antonioni, A, Tomassini, M, and Buesser, P 2014 Random diffusion and cooperation in continuous two-dimensional space. *Journal of theoretical biology*, 344, 40-48.

Barceló, J A and Del Castillo, F (eds.) 2016 *Simulating Prehistoric and Ancient Worlds*. New York: Springer. ISBN: 978-3-319-31481-5

Barceló, J A; Del Castillo, F, Del Olmo, R, Mameli, L, Miguel Quesada, F J, Poza, D and Vilà, X 2014 Social Interaction in Hunter-Gatherer Societies: Simulating the Consequences of Cooperation and Social Aggregation. *Social Science Computer Review*, 32 (3): 417-436. DOI: 10.1177/0894439313511943

Barceló, J A, Del Castillo, F, Del Olmo, R, Mameli, L, Miguel Quesada, F J, Poza, D and Vila, X 2015a Simulating Patagonian Territoriality in prehistory: Space, Frontiers and networks among Hunter-gatherers. In: Wurzer, G, Kowarik, K and Reschreiter, H *Agent-based Modeling and Simulation in Archaeology*. Berlin: Springer-Verlag Advances in Geographic Information Science, pp. 243-289. DOI 10.1007/978-3-319-00008-4__10.

Barceló, J A, Capuzzo, G, Del Castillo, F, Morell, B and Negre, J 2015b Explaining the Adoption of "Innovations" in Western Europe during the Bronze Age: Towards an Agent-Based Simulation. In Giligny, F. et al. *CAA 2014, 21st century Archaeology*. Oxford, ArcheoPress, pp. 623-630. ISBN 978-1-78491-100-3

Cao, Z, Tan, M, Li, L, Gu, N and Wang, S 2006. Cooperative hunting by distributed mobile robots based on local interaction. *IEEE Transactions on Robotics*, 22(2), 402-406.

Conte, R, and Paolucci, M 2014 On agent-based modeling and computational social science. *Frontiers in Psychology* 5. DOI: 10.3389/fpsyg.2014.00668

Cordain, L, Miller, J B, Eaton, S B, Mann, N, Holt, S H A and Speth, J D 2000 Plant-animal subsistence ratios and macronutrient energy estimations in worldwide hunter-gatherer diets. *The American Journal of Clinical Nutrition*, 71(3):682-692.

Del Castillo, M F and Barceló, J A 2012 Why hunter and gatherers did not die more often? Simulating prehistoric decision making. In: Graeme, E; Sly, T; Chrysanthi, A; Murrieta-Flores, P; Papadopoulos, C; Romanowska, I and Wheatley, D. (eds.) *Archaeology in the Digital Era*. Amsterdam: Amsterdam University Press, pp. 154-163. ISBN: 978 90 8964 663 7.

Dyble, M, Thompson, J, Smith, D, Salali, G D, Chaudhary, N, Page, A E and Migliano, A B 2016 Networks of food sharing reveal the functional significance of multilevel sociality in two hunter-gatherer groups. *Current Biology*, 26(15): 2017-2021.

Eaton, S B, Eaton III, S B, and Konner, M J 1997 Review paleolithic nutrition revisited: a twelve-year retrospective on its nature and implications. *European Journal of Clinical Nutrition*, 51(4): 207.

Epstein, J M 2008 Why model? *Journal of Artificial Societies and Social Simulation*, 11(4): 1. <http://jasss.soc.surrey.ac.uk/11/4/12.html>.

Fforde, A 2017 Confirmation bias: methodological causes and a palliative response. *Quality & Quantity*, 51(5): 2319-2335.

Garfinkel, A P, Young, D A, and Yohe II, R M 2010 Bighorn hunting, resource depression, and rock art in the Coso Range, eastern California: a computer simulation model. *Journal of Archaeological Science*, 37(1): 42-51.

Geller, A 2014 Building Empirical Multiagent Models from First Principles When Fieldwork Is Difficult or Impossible. In *Empirical Agent-Based Modelling – Challenges and Solutions.Volume 1: The Characterisation and Parameterisation of Empirical*. New York: Springer, pp. 223-238. DOI 10.1007/978-1-4614-6134-0

Gold, N 2012 Team reasoning, framing and cooperation. Edited by S. Okasha and K. Binmore *Evolution and rationality: Decisions, co-operation and strategic behavior*. Cambridge: Cambridge University Press, pp. 185-212.

Grove, M 2009 Hunter–gatherer movement patterns: Causes and constraints. *Journal of Anthropological Archaeology*, 28: 222–233. DOI: 10.1016/j.jaa.2009.01.003

Gurven, M, Kaplan, H, and Gutierrez, M 2006 How long does it take to become a proficient hunter? Implications for the evolution of extended development and long life span. *Journal of Human Evolution*, 51(5): 454-470.

Hasan, O and Tahar, S 2015 Formal verification methods. In *Encyclopedia of Information Science and Technology*, Third Edition. Hershey, PA: IGI Global, pp. 7162-7170.

Hekkert, M P, Suurs, R A, Negro, S O, Kuhlmann, S, and Smits, R E 2007 Functions of innovation systems: A new approach for analysing technological change. *Technological Forecasting and Social Change*, 74(4): 413-432.

Hill, K 2002 Altruistic cooperation during foraging by the Ache, and the evolved human predisposition to cooperate. *Human Nature,* 13(1): 105-128.

Hill, K, Hawkes, K, Hurtado, M, and Kaplan, H 1984 Seasonal variance in the diet of Ache hunter-gatherers in eastern Paraguay. *Human Ecology*, 12(2), 101-135.

Iwamura, T, Lambin, E F, Silvius, K M, Luzar, J B, and Fragoso, J M 2014 Agent-based modeling of hunting and subsistence agriculture on indigenous lands: understanding interactions between social and ecological systems. *Environmental Modelling & Software*, 58: 109-127.

Janssen, M A and Hill, K 2014 Benefits of grouping and cooperative hunting among ache hunter–gatherers: insights from an agent-based foraging model. *Human Ecology*, 42(6): 823-835.

Janssen, M A and Hill, K 2016 An agent-based model of resource distribution on hunter-gatherer foraging strategies: clumped habitats favor lower mobility, but result in higher foraging returns. In: Barceló, J.A. and M. Del Castillo. *Simulating Prehistoric and Ancient Worlds.* New York: Springer, pp. 159-174.

Keeley, L H 1988 Hunter-gatherer economic complexity and "population pressure": A cross-cultural analysis. *Journal of Anthropological Archaeology*, 7(4): 373-411.

Keene, A S 1979 Economic Optimization Models and the Study of Hunter–Gatherer Subsistence Settlement Systems. In C. Renfrew and K.L. Cooke Transformations: *Mathematical approaches to culture change*. New York: Academic Press, pp. 369-404.

Konner, M and Eaton, S B 2010 Paleolithic nutrition: twenty-five years later. *Nutrition in Clinical Practice*, 25(6): 594-602.

Kremer, M 1993 Population growth and technological change: One million BC to 1990. *The Quarterly Journal of Economics*, 108(3): 681-716.

Lanz, B, Dietz, S, and Swanson, T 2017 Global Population Growth, Technology, and Malthusian Constraints: A Quantitative Growth Theoretic Perspective. *International Economic Review*, 58(3): 973-1006.

Lee, J S, Filatova, T, Ligmann-Zielinska, A, Hassani-Mahmooei, B, Stonedahl, F, Lorscheid, I and Parker, D C 2015 The complexities of agent-based modeling output analysis. *Journal of Artificial Societies and Social Simulation*, 18(4): 4.

Leonard, W R 2014 The global diversity of eating patterns: Human nutritional health in comparative perspective. *Physiology & Behavior*, 134: 5-14.

Lesthaeghe, R 1998 On theory development: applications to the study of family formation. *Population and Development Review*, 24(1):1-14.

Mithen, S J 1988 Modeling hunter-gatherer decision making: complementing optimal foraging theory. *Human Ecology*, 17(1): 59-83.

O'Dea, K 2016 The aboriginal hunter-gatherer lifestyle: Lessons for chronic disease prevention. *Pathology*, 48: S14.

O'Keefe, J H, Vogel, R, Lavie, C J, and Cordain, L 2010 Achieving hunter-gatherer fitness in the 21st century: back to the future. *The American Journal of Medicine*, 123(12): 1082-1086.

Olives Pons, J, Estévez, J, and Vila-Moreno, A 2015 "Agent based simulation of the impact of social discrimination norms on the demographic patterns in Hunter-Fisher-Gatherer Societies", paper presented at the *Eleventh Conference on Hunting and Gathering Societies: Refocusing Hunter-Gatherer Societies*, University of Vienna, Vienna, 7-11 September.

Olives Pons, J, Vila-Moreno, A, and Estévez, J 2018 "Palaeodemography among hunter-fisher-gatherers: a combined and experimental approach to social inequality", paper presented at the *24th European Association of Archaeologist Annual Meeting: Reflecting futures*, Faculty of Geography and History (University of Barcelona) and Centre de Cultura Contemporània de Barcelona (CCCB), Barcelona, 5-8 September.

Packer, C, and Ruttan, L 1988 The evolution of cooperative hunting. *The American Naturalist*, 132(2): 159-198.

Perc, M 2011 Does strong heterogeneity promote cooperation by group interactions?. *New Journal of Physics*, 13(12): 123027.

Pereira, L M and Santos, F C 2012 The emergence of commitments and cooperation. In *Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems-Volume 1.* International Foundation for Autonomous Agents and Multiagent Systems, pp. 559-566.

Peretto, P F and Valente, S 2015 Growth on a finite planet: resources, technology and population in the long run. *Journal of Economic Growth*, 20(3): 305-331.

Perreault, C and Brantingham, P J 2011 Mobility-driven cultural transmission along the forager–collector continuum. *Journal of Anthropological Archaeology*, 30(1): 62-68.

Pontzer, H 2015 Constrained total energy expenditure and the evolutionary biology of energy balance. *Exercise and Sport Sciences Reviews*, 43(3): 110-116.

Rijpma, A and Carmichael, S G 2016 Testing Todd and Matching Murdock: Global data on historical family characteristics. *Economic History of Developing Regions*, 31(1): 10-46.

Ruttan, V W 1996 Sources Of Technical Change: Induced Innovation, Evolutionary Theory And Path Dependence *Bulletins*, 12974, University of Minnesota, Economic Development Center.

Simmen, B, Pasquet, P, Masi, S, Koppert, G J, Wells, J C, and Hladik, C M 2017 Primate energy input and the evolutionary transition to energy-dense diets in humans. *Proceedings of the Royal Society B*, 284(1856): 20170577 DOI: 10.1098/rspb.2017.0577

Skinner, G W 1997 *Family systems and demographic processes*. Chicago, IL: University of Chicago Press.

Skyrms, B 2004 *The stag hunt and the evolution of social structure*. Cambridge: Cambridge University Press.

Skyrms, B 2008 Trust, risk, and the social contract. *Synthese*, 160(1): 21-25.

Smaldino, P E, Newson, L, Schank, J C, and Richerson, P J 2013. Simulating the evolution of the human family: Cooperative breeding increases in harsh environments. *PLoS One*, 8(11): e80753.

Smith, E A 1983 Anthropological applications of optimal foraging theory: a critical review. *Current Anthropology*, 24: 625–651.

Solé, R V, Valverde, S, Casals, M R, Kauffman, S A, Farmer, D, and Eldredge, N 2013 The evolutionary ecology of technological innovations. *Complexity*, 18(4): 15-27.

Stephens, D W and Krebs, J R 1986 *Foraging theory*. Princeton, NJ: Princeton University Press.

Ströhle, A, Hahn, A, and Sebastian, A 2010 Latitude, local ecology, and hunter-gatherer dietary acid load: implications from evolutionary ecology. *The American Journal of Clinical Nutrition*, 92(4): 940-945.

Tomasello, M, Melis, A P, Tennie, C, Wyman, E, Herrmann, E, Gilby, I C and Melis, A 2012 Two key steps in the evolution of human cooperation: The interdependence hypothesis. *Current Anthropology*, 53(6): 673-692.

White, A A 2014 Mortality, fertility, and the OY ratio in a model hunter–gatherer system. A*merican Journal of Physical Anthropology*, 154(2): 222-231.

White, A A 2016 The sensitivity of demographic characteristics to the strength of the population stabilizing mechanism in a model hunter-gatherer system. In Brouwer Burb, M et al. *Uncertainty and Sensitivity Analysis in Archaeological Computational Modeling*. New York: Springer, pp. 113-130.

World Health Organization (WHO) 1991 Energy and Protein Requirements: Report of a Joint FAO/WHO Ad Hoc Expert Committee. Food and Agriculture Organization of the United Nations, Geneva.

Windrum, P, Fagiolo, G, and Moneta, A 2007 Empirical validation of agent-based models: Alternatives and prospects. *Journal of Artificial Societies and Social Simulation*, 10(2): 8.

Winterhalder, B and Smith, E A (eds.) 1981 *Hunter-gatherer Foraging Strategies: Ethnographic and Archaeological Analyses*. Chicago, IL: University of Chicago Press.

Yanow, D and Schwartz-Shea, P 2015 *Interpretation and method: Empirical research methods and the interpretive turn*. New York: Routledge.

Young, D A and Bettinger, R L 1992 The Numic spread: a computer simulation. *American Antiquity*, 57(1): 85–99.