Agent-Based Modeling of the Early Minoan Social Organization Structure

Angelos Chliaoutakis [1] and **Georgios Chalkiadakis** [2]

Abstract. In this work, we develop a generic agent-based model (ABM) for simulating ancient societies. Agents in our model are completely autonomous, in contrast to most existing ABMs used in archaeology. We employ this model to evaluate the impact of different social organization paradigms and agricultural strategies on population viability and evolving spatial distribution of settlement locations, at a particular region of the island of Crete during the Early Bronze Age (early Minoan civilization). Model parameter choices are based on archaeological studies, but are not biased towards any specific assumption. Interestingly, one of the social models examined is inspired by a recent framework for *self-organizing agent organizations*. Results over a number of different simulation scenarios demonstrate an impressive sustainability for settlements adopting a socio-economic organization model based on *self-organization*; while the emerging "stratified" populations are larger than their egalitarian counterparts. This provides support for archaeological theories proposing the existence of different social strata in Early Bronze Age Crete, considering them a pre-requisite for the emergence of the complex social structure evident in later periods. Moreover, observed population dispersion agrees with existing archaeological evidence.

1 Introduction

Agent-based modeling (ABM)[3] is increasingly used in Archaeology in recent years, as a tool for assessing the plausibility of alternative hypotheses regarding ancient civilizations, their organization, and social and environmental processes at work in past ages [4, 14]. Its emerging popularity is due to its ability to represent individuals and societies, and to encompass uncertainty inherent in archaeological theories or findings. Indeed, the unpredictability of interaction patterns within a simulated agent society, along with the possibility of emergent behaviour, can help researchers gain new insights into existing archaeological theories; or even come up with completely novel paradigms regarding the ancient societies being studied.

Now, ABMs should ideally be providing a higher level of abstraction than the one offered by object-oriented systems [12]. Modeled agents should be capable of autonomous action, and of maintaining high-level interactions and organizational relationships with other agents, while being potentially "selfish" [17]. However, most mutiagent-based simulation models used in archaeology, simply do not define agents in the way these are defined in AI or MAS research. Unfortunately, *"agents nowdays constitute a convenient model for representing autonomous entities, but they are not themselves autonomous in the resulting implementation of these models"* [7].

In contrast to most existing ABM approaches in archaeology, agents in our model are completely autonomous, and can build and maintain complex social structures. Furthermore, though our work here is inspired by existing case studies, our model itself is quite generic, and does not aim to prove or disprove a specific theory. Indeed, using agent-based models built on knowledge derived from archaeological records and evidence, but not trying to fit their results to a specific material culture, allows for the emergence of dynamics for different types of societies in different types of landscapes, and can help derive knowledge of socio-ecological systems that are applicable beyond a specific case study.

In more detail, in this work we have developed a functional ABM system prototype for simulating an artificial ancient society of agents residing at the *Malia* area of the island of Crete during the Early Bronze Age. The agents correspond to *households*, which are considered to be the main social unit of production for the period [16]. The ABM allows us to explore the sustainability of agricultural technologies in use at the time, and examine their impact on population dispersion. In addition, the ABM attempts to assess the influence of different *social organization paradigms* on land use patterns and population growth. Importantly, the model evaluates the social paradigm of agents *self-organizing* into a hierarchical social structure, and continuously re-adapting the emergent structure, if required. To this purpose, we developed and tested a *self-organization algorithm* that builds on the work of [15] on self-organizing agent organizations used for problem-solving and task execution. We note that this is the first time a self-organization approach is incorporated in an ABM system used in archaeology.

Our simulation results demonstrate that self-organizing agent populations are by far the most successful, growing much larger than populations employing different social paradigms. The success of this (dynamic) social paradigm that gives rise to *"stratified"*, that is, non-egalitarian societies, provides support for so-called *"managerial"* archaeological theories which assume the existence of different social strata in Neolithic / Early Bronze Age Crete; and consider this early stratification a pre-requisite for the emergence of the Minoan Palaces, and the hierarchical social structure evident in later periods [2, 9]. In addition, the observed dispersion of settlements is in line with existing archaeological data.

2 Related work

In recent decades, archaeologists have used computer models to test possible explanations for the rise and fall of complex ancient societies. They now begin to use multiagent simulations as a means for

[1] Technical University of Crete, Greece, email: angelos@intelligence.tuc.gr, secondary affiliation: GeoSat ReSeArch Laboratory - IMS/FORTH, Greece
[2] Technical University of Crete, Greece, email: gehalk@intelligence.tuc.gr
[3] ABM acronym denotes "agent-based modeling" and "agent-based model".

incorporating spatial information into their models. An example of such a system, and, indeed, a success story, is the study of the cause of the collapse of the Anasazi, around 1300 CE in Arizona, USA [4]. Scholars have argued for both a social and an environmental cause (drought) for the collapse of this society. Simulating individual decisions of households on a very detailed landscape of physical conditions of the local environment, the authors of [4] refute the hypothesis that environmental factors alone account for the collapse. Another study was conducted for the region of the Long House Valley in Arizona, on the reasons why there have been periods when the Pueblo people lived in compact villages, while in other times they lived in dispersed hamlets [14]. The model results show the importance of environmental factors related to water availability for these settlement changes. Moreover, a model for understanding how prehistoric societies adapted to the prehistoric American southwest landscape was proposed in [11]. That agent-based model could explore to some extent how various assumptions concerning social processes affect the population aggregation and size, and the dispersion of settlements.

Regarding the concept of *self-organization* [5], it is inspired from natural systems which function without any external control, and adapt to changes in the environment through spontaneous reorganization. This self-organizing ability makes these natural systems robust to changing environmental conditions, thus enhancing their survivability. In the context of computing systems, self-organization refers to the process of the system autonomously changing its internal organization to handle changing requirements and environmental conditions. Several approaches have been explored by researchers for developing self-organizing multiagent systems. Intuitively, in social self-organization methods like the one in [15], adaptation targets organization-wide characteristics, such as *structure*, rather than the individual agent ones. Changing the characteristics and internal configurations of specific agents may not be possible on all occasions due to physical and accessibility limitations, and such changes might be beyond the control of the agents themselves. Moreover, in dynamic environments modeling real human societies, continuous *structural self-adaptation* is a necessity, in the face of uncertainty and ever-present change [6]. Therefore, a structural adaptation method is preferable to methods modifying particular agent properties, and enables the agents to choose when and how to adapt—especially when placed in real world, ever-changing environments.

3 The Agent-Based Model

Agents in our model correspond to *households*, each containing up to a maximum number of *individuals*. Each household agent resides in a *cell* within the environmental grid, with the cell potentially shared by a number of agents. Adjacent cells occupied by agents make up a *settlement*—and there is at least one occupied cell in a settlement. Each agent cultivates a number of cells located next to the settlement.

The model then operates as follows: at every time step corresponding to a period of *one year*, agents (i.e., households) first harvest resources located in nearby cells (corresponding to the fields they are cultivating). Then, they check whether their harvest (added to any stored resource quantities) satisfies their minimum perceived needs. If not, they might ask others for help (depending on the social organization model in effect), or they might even eventually consider moving to another location. When the *self-organization* social paradigm is in use, the agents within a settlement continuously re-assess their relations with others, and this leads to "social mobility" affecting the way resources are ultimately distributed.

Population size affects the land productivity in two ways: positively, since the continuous occupation or cultivation of an area by a large populace leads to experience and subsequent higher crop yield; and negatively, since the soil quality of lands cultivated continuously by a large population degrades due to erosion processes. Population levels at a given area are affected by migration, as well as natural population change by birth and death of agents. Lower amount of resources reduces birth rate, and thus leads to a reduced population size and threatens the agents with extinction.

3.1 Environment

Agents and resources are located within a two dimensional space, specified in terms of coordinates and cells. The spatial resolution is 20×25 km area with a 100×100 m cell size for the grid space. Thus the landscape consists of 50K cells, the time slot investigated is $\approx$ 2,000 years (3,200 to 1,200 BCE), with annual time steps.

Resources exist in cells at fixed locations, and they may vary with respect to the amount of energy they embody, and their availability through time. The productivity of an individual cell (in *kg*) is a function of the cell's geo-morphological characteristics (in particular, land slope) given its location on the map, and the *soil fertility*, which depends on the amount of labour applied on the cell by the agents. With more labour applied on the cell, there is a modest increase in returns (as agents get better in preparing the land and harvesting the resource). Furthermore, the production quality of a cell depends on the relative soil quality. With increasing use, cell soil quality is reduced due to erosion processes. Soil depletion depends on settlement population size: a higher population puts more anthropic pressure on the land. This mimics loss of nutrients, vegetation, and other resources.

To model these dependencies, we devised a function Q_i to describe the *agricultural production quality* of a cell i:

$$Q_i\left(P\right) = \alpha_i \left(\frac{2\mu - 4\mu_{max}}{{P_{max}}^2} P^2 + \frac{4\mu_{max} - 3\mu}{P_{max}} P + \mu \right) \quad (1)$$

where P is the current *population size* of the corresponding settlement[4] μ is the *initial amount of resources* of the cell, μ_{max} is the *maximum resource level* per cell, P_{max} is the *maximum possible settlement population size*, and α_i is a real valued weight in $[0, 1]$, characterizing the agricultural production quality of cell i. Intuitively, α_i represents the land suitability of a cell for agriculture. There are no agricultural activities in areas with slope more than 45^o (still being generous). Thus, α_i is derived from an exponential decay function of the cell's slope degree with a decay constant of 20 (so that a value of more than 45^o is prohibitive).

Equation 1 captures the fact that labour applied on a field increases crop yield up to a point, but at the same time a household cannot productively use a location forever (due to soil depletion). It was inspired by the logistic map equation, which is the discrete version of the logistic differential equation widely used to model population growth. In our experiments, a cell's production output Q_i at a random run (corresponding to 2,000 years) is multiplied with a sample from a standard normal distribution, and thus varies from run to run.

Moreover, there are two agricultural technologies the agents can use *(i) Intensive Agriculture*, where agents cultivate intensively the

[4] In Eq. 1 we let the settlement's population P influence the amount of labour applied on a cell, since field cultivation was in many respects communal in those times. Regardless of that assumption's validity, this value is essentially "normalized" by the maximum possible population; thus the Q_i function's desired behaviour would have been entirely similar had we used the household size instead of the settlement population. Moreover, this function is used by all competing social organization methods in our experiments, thus granting none of them an unfair advantage.

neighbouring land area leading to greater production per hectare. The output associated with *intensive agriculture* in our model is 1500 *kg / ha* [10], and *(ii) Extensive Agriculture*, where agents "expand" their cultivated areas, using more land but producing less per hectare. Archaeologists believe that *extensive* agriculture is representative of socially non-egalitarian contexts associated with later Bronze Age Minoan palaces, where cultivation tillage (agricultural preparation) was done by ox-drawn plough or ards [10]. The production associated with *extensive agriculture* is 1000 *kg / ha* [10].

3.2 Agents

Agents seek to "*stay alive*" by acquiring and consuming resource energy. Acquiring energy is the only inbuilt goal of the agents. The utility U_x of the agent x, corresponding to the total harvested resource amount of that agent, is given by the following function (assuming the agent cultivates n environmental cells):

$$U_x = \sum_{k=1}^{n} Q_k \tag{2}$$

Note that due to Equation 1 the utility of agent x depends on the agricultural quality of the cells it cultivates. In our work here, the only technology influencing the agent utility is agriculture, as this was assumed, for simplicity, to be the main activity sustaining the early Minoan civilization. The model can be readily extended, however, to incorporate utility gained by other means.

Now, an agent needs to be receiving some minimum utility from its cultivated cells, in order to be fit enough to procreate (we elaborate on this below). The minimum utility (minimum level of resources) for household agent x containing j individuals is calculated as $U_x^{thres}=j \times res_{min}$; with res_{min} being the *minimum amount of resources* (in *kg*) required by an individual per year (this value is set based on archaeological research estimating the average yearly food consumption per person during the era in question).

Moreover, agents employ actions by which they may interact with the environment (*agent-environment* actions). Apart from generating an offspring or dying, they may cultivate the land over time, or migrate to another location, if an agent's current location does not fulfil the agent demands. Specifically, the *agent – environment* actions are *(i) Hatching*, where a household agent may generate an offspring with some probability (see below). When an agent generates an offspring, a newborn individual is added. If the new size of the household is higher than the defined maximum number of individuals per household, a new agent is created (agent offspring) by splitting the old household in two random sizes in the same environmental cell. If, by doing so, the maximum number of agents per cell is reached, the newly created household (agent) is located in any adjacent cell that has fewer agents than the maximum possible. These parameters are set at initialization, using existing archaeological estimates. *(ii) Cultivation*, where an agent may cultivate the land within a specified range from its settled location and stores any "surplus" resources in their *storage*, for up to y years. The number of cells a household cultivates depends on its size. For example, a household agent x with $j = 7$ individuals adopting an extensive agricultural strategy (which produces 1000 kg/cell), needs to accumulate $U_x^{thres} = 7 \times 250 = 1750$ kg of food resources for the current year, assuming $res_{min} = 250$ kg. Therefore, the agent chooses two (unoccupied) nearby cells ($2 \times 1000 = 2000$ kg) from its settled location for cultivation ($k = 2$). If $U_x > U_x^{thres}$ that year, then the surplus resource amount of $U_x - U_x^{thres}$ is kept in the agent's *storage* for future use. If an agent does not receive the minimum level of resources it requires, U_x^{thres}, for y years in a row (and the *storage* is empty), it considers moving to another location. The range of resource cells where an agent may cultivate, depends on the maximum harvest amount of agricultural regime defined, and the total number of inhabitants in the settlement. A farming area cannot exceed a number of cells $n =$ number of inhabitants $\times res_{min}$ (kg) / agricultural regime amount (kg/ha). *(iii) Migration*. An agent x moves to another location only when it finds a location within a radius r_{max} that is better than its own location. The agent calculates its expected utility U_x for the new location at time step $t + 1$, as the average *agricultural production quality* of the neighbouring cells which is defined by Equation 1, considering the agent moved to the respective "unused" cell (i.e., a cell that is not contained in a settlement, and does not correspond to cultivated land from any other agent). An agent may also migrate to a cell within another established *settlement*; in that case, it first considers the average expected utility of agents in the settlement in question. If the agent's expected utility U_x' for the new location is higher than its current utility U_x, the location is considered to be an option. If there are many such locations, the agent migrates to the one perceived to be most favourable.

Agents also have actions by which they interact with each other. These *agent-agent* actions correspond to distinct *behavioural modes* or *social organization paradigms*, describing the way by which the distribution of harvested resources takes place among the population. In our work here, we examine three different behavioural modes *(i) Independent*, where agents act independently and there is no sharing of harvest or stored resources among the agents. *(ii) Sharing*, an egalitarian society paradigm, by which agents may share energy amounts within a settlement. All storage and harvest is pooled each year and distributed equally among the agents, and *(iii) Self-Organized*, where agents re-arrange their (hierarchical) structure autonomously, without any external control, in order to adapt to changes in requirements and environmental conditions. In other words, they constantly evaluate and possibly alter the *relations* or *links* with other agents; these relations determine the way resources are ultimately allocated. We elaborate on this in Section 4 below.

The total number of agents in the system changes over time, as individuals belonging to households are born or die. The death rate for an individual belonging to a household is defined as $deathrate = 0.002$; while the agent procreation ability (determining the annual levels of births) is based on the amount of food consumed by the agent during the year. Specifically, the birth rate is given by[5]:

$$birthrate = r_{birth} * \hat{U}_x / U_x^{thres}$$

with r_{birth} equal to 0.003, where $\hat{U}_x$ is defined as follows:

$$\hat{U}_x = \begin{cases} U_x, & \text{if } U_x < U_x^{thres} \\ U_x^{thres}, & \text{if } U_x \geq U_x^{thres} \end{cases}$$

However, whenever $U_x < U_x^{thres}$, the agent attempts to "replenish" U_x by acquiring resources by its storage (or, if the self-organization social model is in use, maybe by acquiring resources from other agents). These rates produce a *population growth rate* (= birth rate - death rate) of 0.001=0.1%, when households consume adequate food quantities. This corresponds to estimated world-wide population growth rates during the Bronze Age, according to [3].[6]

[5] The birth rate is modeled as in [11], and is higher for more wealthy households, capturing the fact that these can survive longer then poorer ones.

[6] Others estimate growth rates in mainland Greece and the Aegean to be between 0.1 to 0.4% per year, for long periods during the Bronze Age [1].

4 Self-Organization

The rise of complex, hierarchical societies presents itself as an evolutionary advance. Complex societies have larger populations than their egalitarian predecessors and deploy more powerful productive forces. The emergence of the palaces in the Cretan Early Bronze Age marks a transition from an egalitarian to a more complex, state-like society with a clear hierarchical structure crowned by a central, administrative authority [2]. In our work here we examine whether the adoption of a self-organized agent settlement organization will indeed give rise to a stratified social structure—which will also be able to sustain itself through time. In effect, the self-organization technique presented here is one that results to the continuous *targeted redistribution of wealth*, so that resources flow from wealthy to poor agents, when needed. This will become clear below. Our self-organization model is inspired by the work of [15]. However, we modify that model in several important ways.

4.1 Agent interactions and relations

Agents may improve their performance as a group (vitality of the settlement) by modifying the social structure through changes to their relations (*re-organization*) continuously over time. They need to interact with one another for the proper allocation of resource needs. A shortage of resource amount where, $U_x^{thres} - U_x > 0$, gives rise to a *task* for agent x: the agent needs to *accumulate produce equal to the perceived deficit*. Tasks emerge at random time-steps and the processing of a task begins with its assignment to that agent. Agents perform three types of self-organization actions: *(i) execution*, *(i) allocation*,and *(iii) adaptation*. An agent may *execute* a task (by consuming resources in its storage), or *reallocate* the task to another agent. If agent x cannot execute the task (*storage* = 0), it *reallocates* the task to another capable agent y. Task execution then means that y delivers to x a resource amount, by taking that out of its own storage. If y is only able to replenish a portion of the requested resources, this is considered a *subtask execution*. Note that capable agents in our model (i.e., those with *storage* $>$ 0) always accept task allocations or executions; this is due to an assumption of high degree of cooperation among households in Early Bronze Age Minoan societies [13]. Thereafter, agents reorganize and *adapt* their relations, maintaining a stratified social structure.

Agent interactions are therefore regulated by the settlement's social structure, with relations among agents described as: *(i) acquaintance* (aware of the presence, but having no interaction); *(ii) peer* (low frequency of interaction); and *(iii) authority* (*superior – subordinate* relations, where agents have high frequency of interaction).

4.2 Decision making and adaptation

Mirroring the work of [15], our algorithm has two main stages: the *task execution* mechanism, and the *re-organization (decentralized structural adaptation)* one. The steps of the task execution mechanism are as follows: *(i)* when an agent needs to execute a task, it will allocate the task (or subtask) to self if possible (*storage* $>$ 0); otherwise, it will try to allocate the task to one of its capable *superiors* (choosing among such superiors randomly). *(ii)* if neither the agent itself nor its superiors are capable of executing the task, then the agent tries to reassign it (the whole task or the remaining subtask) to one of its *peers*. *(iii)* if none of its peers is capable of the task either, the agent will try to allocate it to one of its *subordinates*, who must in turn find other superiors or peers to allocate the task to, and *(iv)* when all these fail, the agent checks among its acquaintances for a capable agent, and tries to form a subordinate relation with it.

In every assignment of a task to a capable agent, execution (offering of stored resource amount) takes place, where the storage and utility values of the corresponding agents are updated. An agent assigns tasks initially to its superiors. In this way, agents with $U = U^{thres}$ and *storage* $>$ *0* shall always be on the top of the settlement structure (*elite / authority*), and will help support subordinate (poorer) agents (i.e., agents with $U < U^{thres}$ and *storage = 0*). Therefore, an agent in need mostly assigns tasks to its superiors and seldom to its peers or subordinates. Thus, the structure of a settlement organization influences the allocation of tasks.

Every task execution action has an associated *load*. The total load l_x added onto x by all other agents, is the sum of its resources that were given out to others in that time-step:

$$l_x = \sum_{t \in T_x} res_t \tag{3}$$

where res_t is the resource amount expended by agent x for executing task t and T_x is the set of the total tasks executed by x in that time-step within the organization. We also denote by $T_{x,y}$ the number of tasks assigned to agent x by agent y; and by $l_{x,y}$ the load added onto x solely by assignments from y. Loads on the various agents are assumed to be known to everyone in the community.

Now, agents use the information about all their current year allocations to re-evaluate their relations with their subordinates, superiors, peers and acquaintances. This evaluation is performed during the re-organization stage, and is based on examining the overall load between two agents, in case the relation had been different than the current one. As mentioned already, the relation between every pair of agents x and y has to be in one of the following *states*: *acquaintance*, *peer* and *authority*. An *authority* relation means that there is a relative difference in the amount of load per assigned tasks between them; a superior (wealthier) agent has more tasks assigned, while the subordinate agent (in need) has less. A *peer* relation instead implies a relatively equal amount of load per agent. At a given state, agent y evaluates a set of possible reorganization (adaptation) actions:

1. when y is an acquaintance of x: (i) $form\_peer_{x,y}$, denoting the formation of a *peer* relation between the agents, (ii) $form\_auth_{x,y}$, denoting the formation of an *authority* relation, where y is subordinate of x; and (iii) *no_action*.
2. when y is a subordinate of x: (i) $rmv\_auth_{x,y}$, denoting the removal of their *authority* relation and the formation of an *acquaintance* relation (ii) $rmv\_auth_{x,y} + form\_peer_{x,y}$, denoting the removal of their *authority* relation and the formation of a *peer* relation between the agents; and (iii) *no_action*.
3. when y is a peer of x: (i) $rmv\_peer_{x,y}$, denoting the removal of their *peer* relation and the formation of an *acquaintance* relation (ii) $rmv\_peer_{x,y} + form\_auth_{x,y}$, denoting the removal of their *peer* relation and the formation of an *authority* relation between the agents, where y is subordinate of x; and (iii) *no_action*.
4. when y is a superior of x: (i) $rmv\_auth_{y,x}$, denoting the removal of their *authority* relation and the formation of an *acquaintance* relation (ii) $rmv\_auth_{y,x} + form\_peer_{x,y}$, denoting the removal of their *authority* relation and the formation of a *peer* relation between the agents; and (iii) *no_action*.

Reorganization actions are deterministic, and are selected by the agents according to their calculated utility. The utility for agent y of performing an action a modifying its relation with x at a given state, is provided by an action evaluation function V with the general form:

$$V(a, x, y) = \pm rdLoad_{x,y} \pm R \quad (4)$$

where $rdLoad_{x,y}$ is the *relative difference* between the current load on x and the current load on y (per task); and R, an adequate *ratio limit* (%) for this difference to be evaluated in order to estimate the expected utility for changing an existing relation. Intuitively, combined with R, the *relative difference* is used as a quantitative indicator of quality assurance and control, for the repeated evaluation of agent relations. For example, acquaintances x and y may form an authority relation as long as their relative load difference per task is greater than the limit ratio R, while they may form a peer relation when their relative load difference is less than this ratio limit R.

Table 1 lists the evaluation functions for the five "atomic" actions. In the case of the "composite" actions ($rmv\_peer + form\_auth$ or $rmv\_auth + form\_peer$), the value is simply the sum of the individual evaluations of the comprising actions.

Now, the *main* modifications[7] *wrt.* the self-organization algorithm in [15] are the following. First, during decision making, an agent assigns tasks initially to its *superiors* rather than its *subordinates*. This is because superiors correspond to the emerging elite which possesses surplus resources that it could potentially distribute to the poorer strata. Second, we use a simple, distinct state transition value function V. Our self-organization method aims to facilitate a targeted redistribution of wealth. Given this, the value function V employs the notion of a *relative* load difference among agents (this is not done in [15]). Finally, the load associated with a task here is equal only to the resources amount offered. In particular, there is no "reorganization load" when agents reason about changing a single relation with all the agents in the settlement, neither a "management load"; agents in our model do not have "limited computational capacities", neither "communication costs". This is natural, since agents forge relations only with neighbours within the settlement.

5 Experiments and Evaluation

The ABM model was developed using the *NetLogo*[8] modeling environment. The identified model parameters were initialized to values set so that they correspond to estimates found in archaeological studies. The *number of agents* is derived from the user-defined variables of maximum number of individuals/cell (default: 100, since this is an estimated per hectare population in an agricultural settlement [10]), divided by the maximum number of inhabitants/household (default: 10) as a random number given between 1 and 10 (100/10). The agent can store some resource amount for a number of (user-defined) *years of storage* (value used in our experiments: 5 years). The figure of 250 kg was used as the *minimum amount of resources* required per individual per year (res_{min}), based on [10]. Moreover, the initial level of the environmental resources is defined as the agricultural production quality Q_i of a cell i (Eq. 1). Initial households and settlement locations are (pseudo) randomly initialized. The *number of settlements* is user-defined (default: 2). The *distance agents can move/migrate* to in one time step is also user-defined (default: r_{max} = 3 km), while an agent senses only agents within the settlement area. As mentioned, an agent makes decisions based on one of the three different social behaviour modes: *independent*, *sharing* and *self-organized*. For the later, the ratio limit *R* is user-defined (default: *R* = 60%).

Various scenarios were taken into account for the experimental setup, with different parameterization for: three different behavioral modes (i.e., the social organization paradigms used); two different agricultural regimes; and, since spring locations in current days still bear some relationship to the location of springs during the Minoan times, the proximity of a new location to an aquifer (spring, river or coast) may also be taken into account [8]. When aquifer proximity is taken into account, the initial production μ of a cell receives a penalty up to a percent of its value, with cells located outside a 1,250m radius from the aquifer receiving a 100% initial production penalty. The exact penalty value for cells within the aforementioned radius, is provided by performing a *density analysis* of those locations, a spatial analysis tool that can calculate the density of input features (springs, rivers, sea/coastline) within a radius around each environmental cell.[9] Since there is no past vegetation data available, at the beginning of each scenario resources were spread randomly over the land, but with resource amounts at a particular cell depending on its slope (as discussed in Sec. 3).

Each scenario was simulated for thirty runs, generating a total of 360 simulations. We state here again that the only activity or force affecting the population dynamics in our simulations was agriculture — and the social organization paradigm used.

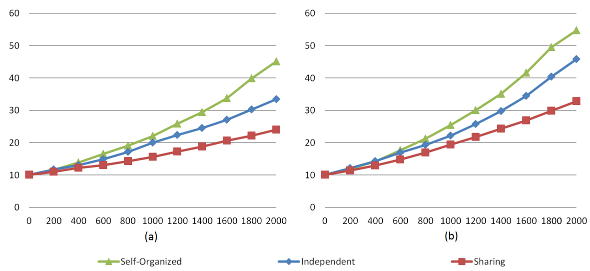

Figure 1. Population size over 2000 years. *(a)* for Intensive Agriculture where aquifer proximity is considered; and *(b)* for Extensive Agriculture where no aquifer proximity is considered.

Population growth results with respect to the *intensive* agricultural strategy and the *extensive* agricultural regime are shown in Figs. 1(a) and (b). Due to space restrictions, results for *intensive* agriculture where no aquifer proximity is considered as well as for *extensive* agriculture where aquifer proximity is considered are not shown here; however, they are entirely similar to those in Fig. 1. The figures indicate that self-organized societies thrive under both regimes. The results thus appear to support the case for archaeological theories assuming the existence of a hierarchy-based economy and social model, one giving rise to different social strata ("stratification"); and the belief that stratification precedes the development of centers for higher-order regulation by several centuries [9]. It is also clear that societies adopting a self-organization strategy are better-off irrespective of whether aquifer proximity is taken into consideration or not.

We also report some results on the density and spatial distribution of settlements over the area of interest. These are shown in Figure 2. The figure depicts final settlement locations after 2000 years (averaged over all 30 runs for a particular scenario), buffered with a radius proportional to the years settled (last 500 years). Regardless of

[7] There are other minor differences with the work of [15]. For instance, in our model we replace the notion of the number of time-steps that an agent has *waiting tasks*, with that of an agent having $U < U^{thres}$ (and *storage* = 0). We do not list these minor differences here.

[8] See *http://ccl.northwestern.edu/netlogo*.

[9] See *http://resources.arcgis.com/*.

Table 1. Atomic reorganization actions, and corresponding action evaluation functions.

Action	Action evaluation function used
$a = form\_auth_{x,y}$	$V(a) = \left(\frac{l_x}{T_x} - \frac{l_y}{T_y}\right)/\max\left\{\frac{l_x}{T_x}, \frac{l_y}{T_y}\right\} - R$, if $T_x + T_y > 0$; else $V(a) = -1$
$a = rem\_auth_{x,y}$	$V(a) = -\left(\frac{l_{x,y}}{T_{x,y}} - \frac{l_{y,x}}{T_{y,x}}\right)/\max\left\{\frac{l_{x,y}}{T_{x,y}}, \frac{l_{y,x}}{T_{y,x}}\right\} + R$, if $T_{x,y} + T_{y,x} > 0$; else $V(a) = -1$
$a = form\_peer_{x,y}$	$V(a) = -\left\lvert\frac{l_x}{T_x} - \frac{l_y}{T_y}\right\rvert/\max\left\{\frac{l_x}{T_x}, \frac{l_y}{T_y}\right\} + R$, if $T_x + T_y > 0$; else $V(a) = -1$
$a = rem\_peer_{x,y}$	$V(a) = \left\lvert\frac{l_{x,y}}{T_{x,y}} - \frac{l_{y,x}}{T_{y,x}}\right\rvert/\max\left\{\frac{l_{x,y}}{T_{x,y}}, \frac{l_{y,x}}{T_{y,x}}\right\} - R$, if $T_{x,y} + T_{y,x} > 0$; else $V(a) = -1$
$a = \ no\_action$	$V(a) = 0$

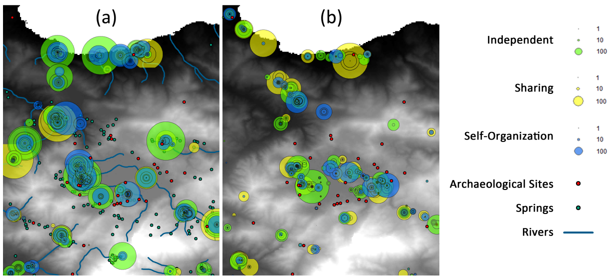

Figure 2. Settlement location buffers after 2000 years. *(a)* when *Intensive* Agriculture is used where aquifer proximity is considered; and *(b)* when *Extensive* Agriculture is used where no aquifer proximity is considered.

aquifer proximity or agricultural strategy (*intensive* or *extensive*) employed, settlements are concentrated near actual (depicted) archaeological sites in the coastal regions or at the Lassithi plateau (the gray area in the middle of the modeling area in Figure 2).

6 Conclusions and Future Work

In this work we developed an agent-based modeling system for archaeology research, and employed it to gain new insights into the social organization and agricultural activities of Minoan households residing at the Malia area in Crete during the Bronze Age. To that end, we incorporated, for the first time in an archaeology simulations system, an appropriately modified *self-organization* method originally proposed for modern-day agent organizations. Interestingly, our simulation results indicate that a social model based on continuously readapted relations among Minoan households might well have existed in the area of study. The self-organization model gives rise, naturally, to implicit agent hierarchies. As explained in section 4, however, the wealthy are assumed to be helping out agents in need. Thus, these results could be interpreted as an indication that *targeted wealth redistribution* works better than a blind one.

Our prototype ABM is based on archaeological evidence, and is meant to be used as a tool enabling archaeology researchers to assess the potential validity of competing hypotheses; or even consider aspects of the past that have not yet been thought of. The system is generic and fully parameterized, and allows for the easy incorporation of new data or alternative theories. It can therefore potentially be employed to model different civilizations, areas, and eras. Last but not least, it can provide the basis for a fully interactive tool, to help popularize archaeological theories. In terms of future work, we need to run more scenarios with a variety of initialization setups. We also intend to equip the ABM with additional modules (vegetation data, soil depth, geological information, other archaeological evidence or scenarios of interest) and additional types of utility-generating activities, and to examine the economic and political interactions among settlements (as opposed to those among households alone).

REFERENCES

[1] J. Lawrence Angel, 'The bases of paleodemography', in *American Journal of Physical Anthropology*, volume 30, (1969).

[2] John Cherry, 'Polities and Palaces: Some Problems in Minoan State Formation', in *Peer Polity Interaction and Socio–Political Change*, 19–45, Cambridge University Press, (1986).

[3] G. L Cowgill, 'On the causes and consequences of ancient and modern population changes', *American Anthropologist*, **77**(3), 505–525, (1975).

[4] J. S. Dean, G. J. Gumerman, J. M. Epstein, R. L. Axtell, A. C. Swedlund, M. T. Parket, and S. McCarroll, 'Understanding Anasazi cultural change through agent-based modeling', in *Dynamics in Human and Primate Societies*, 179–206, (2000).

[5] G. Di Marzo Serugendo, M.P. Gleizes, and A. Karageorgos, 'Self-organisation and emergence in multi-agent systems: An overview', *Informatica*, **30**(1), 45–54, (2006).

[6] Virginia Dignum, Frank Dignum, and Liz Sonenberg, 'Towards dynamic reorganization of agent societies', in *Proc. of ECAI Workshop on Coordination in Emergent Agent Societies*, pp. 22–27, (2004).

[7] Alexis Drogoul, Diane Vanbergue, and Thomas Meurisse, 'Multi-agent based simulation: Where are the agents?', in *Multi-agent-based simulation II*, 1–15, Springer Berlin Heidelberg, (2003).

[8] Ricardo Fernandes, Geert Geeven, Steven Soetens, and Vera Klontza-Jaklova, 'Mapping the probability of settlement location for the Malia-Lasithi region (Crete, Greece) during the Minoan Protopalatial period', in *Landscape Archaeology between Art and Science: From a Multi to an Interdisciplinary Approach*, p. 524, (2012).

[9] Antonio Gilman, 'The Development of Social Stratification in Bronze Age Europe', *Current Anthropology*, **22**(1), (1981).

[10] V. Isaakidou, 'The fauna and economy of Neolithic Knossos revisited', in *Escaping the Labyrinth. The Cretan Neolithic in Context. Sheffield Studies in Aegean Archaeology*, 90–114, Oxbow Books, Oxford, (2008).

[11] M. A. Janssen, 'Population aggregation in ancient arid environments', *Ecology and Society*, **15**, 19, (2010).

[12] Nicholas R. Jennings, 'On agent-based software engineering', *Artificial Intelligence*, **117**(2), 277 – 296, (2000).

[13] S. Jusseret, J. Driessen, and Q. Letesson, 'Minoan lands? some remarks on land ownership in bronze age crete', in *An Archaeology of Land Ownership*, 46–49, Cambridge University Press, (2013).

[14] T. A. Kohler, J. Kresl, C. V. West, E. Carr, and R. H. Wilshusen, 'Be there then: A modeling approach to settlement determinants and spatial efficiency among late ancestral pueblo populations of the Mesa Verde region, U.S. Southwest', in *Dynamics in Human and Primate Societies*, 145–178, (2000).

[15] R. Kota, N. Gibbins, and N. R. Jennings, 'Self-Organising Agent Organisations', in *Proc. of the 8th Int. Conf. on Autonomous Agents and Multiagent Systems (AAMAS-2009)*, pp. 797–804, (2009).

[16] T. Whitelaw, 'House, households and community at Early Minoan Fournou Korifi: Methods and models for interpretation', in *Building Communities: House, Settlement and Society in the Aegean and Beyond*. British School at Athens Studies, (2007).

[17] M. Wooldridge and N. R. Jennings, 'Intelligent agents: theory and practice', *The Knowledge Engineering Review*, (1995).