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Agent-based modeling of ancient societies and their organization structure

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Abstract Some of the most interesting questions one can ask about early societies, are about people and their relations, and the nature and scale of their organization. In this work, we attempt to answer such questions with approaches introduced by multiagent systems. Specifically, we developed a generic agent-based model (ABM) for simulating ancient societies. Unlike most existing ABMs used in archaeology, our model includes agents that are autonomous and utility-based. Our model can (and does) also incorporate different social organization paradigms and technologies used in ancient societies. Equipped with such paradigms, our model allows us to explore the transition from a simple to a more complex society by focusing on the historical social dynamics—i.e., the flexibility and evolution of power relationships depending on social context and time. As a case study, we employ our model to evaluate the impact of the implemented social and technological paradigms on an artificial Early Bronze Age "Minoan" society located at a particular region of the island of Crete. Model parameter choices are based on archaeological evidence and studies, but are not biased towards any specific assumption. Results over a number of different simulation scenarios demonstrate an impressive sustainability for settlements consisting of and adopting a socio-economic organization model based on *self-organization*, and which was inspired by a recent framework for modern *self-organizing agent organizations*. This is the first time a self-organization approach is incorporated in an archaeology ABM system.

Keywords Self-organization · Multi-agent systems · Agent-based modeling · Social archaeology

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1 Introduction

Agent-based modeling (ABM)[1] began as the computational arm of *artificial life* some 20 years ago. The essential features of artificial life models are translated into computational algorithms through ABM, since it is concerned with exploring and understanding the processes that lead to the emergence of order through computational means. The past decade has seen *archaeology* taking an increasingly high interest in ABM [16,20,36,43]. Its emerging popularity is due to the ABM's 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 strong possibility of emergent behaviour, can help archaeology researchers gain new insights into existing theories; or even come up with completely novel explanations and paradigms regarding the ancient societies being studied. ABM is therefore seen by archaeologists as a powerful tool for assessing the plausibility of alternative hypotheses regarding ancient civilizations, their social organization, and social and environmental processes at work in past ages.

Now, *multiagent systems (MAS)* research has always been advocating that ABMs should be providing a higher level of abstraction than the one offered by object-oriented systems [39]. Modeled agents should be capable of autonomous action, and of maintaining high-level interactions and organizational relationships with other agents, while being potentially "selfish" [69]. However, most multiagent-based simulation models used in archaeology, simply *do not* define agents in the way these are defined in AI or MAS research. Unfortunately, "*agents nowadays constitute a convenient model for representing autonomous entities, but they are not themselves autonomous in the resulting implementation of these models*" [21]. To the best of our knowledge, and with the possible exception of only two approaches, mentioned in Sect. 2 below, existing ABMs used in archaeology do not incorporate truly autonomous, utility-maximizing agents in their models. Moreover, while certain ABMs used in archaeology have demonstrated an ability to both describe population dynamics within a specific region, and reproduce existing archaeological records, they have also been criticized for allowing to be entirely driven by input data, or for adjusting the carrying capacity of the simulated landscape in order to better fit a given hypothesis (see, e.g., such a discussion in [36]).

By contrast, two central aims of our work in this paper were *(a)* to put forward a model that is generic, in the sense that it can be employed for the study of practically any society of choice, and can easily incorporate and help test any theories proposed by archaeologists (or social scientists); and *(b)* to showcase how MAS-originating concepts, techniques, and algorithms can be incorporated in archaeology ABMs. Thus, unlike most existing ABM approaches in archaeology, which employ a simple reactive agent architecture, we apply a *utility-based* agent architecture in our model.[2] Our agents act autonomously towards utility maximization, and can build and maintain complex social structures. Furthermore, though it is inspired by existing models and specific case studies, our model is quite generic, can (demonstrably) incorporate a number of different social organization paradigms and various (e.g., agricultural) technologies, and does not aim to prove or disprove a specific theory. Indeed, using agent-based models that were built on knowledge derived from archaeological research, but do not attempt to fit their results to a specific material culture, allows for the

[1] We will be using the acronym ABM to refer to both "agent-based modeling" and "agent-based model(s)".

[2] We note that by doing so we do not mean to argue that utility is the main factor driving human behaviour or the advance of human societies. Nevertheless, utility-based agents and utility theory have long been adopted as useful tools in the MAS community [56,68].

emergence of dynamics for different types of societies in different types of landscapes, and can help derive knowledge of socio-economic and 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[3] for simulating an artificial ancient society of autonomous agents residing at the *Malia* area of the island of Crete during the Early Bronze Age. In our work, the ABM allows us to explore the sustainability of specific agricultural technologies in use at the time, and examine their impact on population size and dispersion; and it allows for the incorporation of any other technology that needs to be modeled. In addition, it allows us to assess the influence of different *social organization paradigms* on land use patterns and population growth. Importantly, the model incorporates the social paradigm of agents *self-organizing* into a "stratified" 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 Kota et al. [44,45] on modern *self-organizing agent organizations* (used for problem-solving and task execution). The self-organization algorithm incorporates a set of *agent relations* influencing the various social interactions, and a *decentralised structural adaptation* mechanism, suitable for open and dynamic organizations. We note that this is the first time a self-organization approach is incorporated in an ABM used in archaeology.

Simulation results demonstrate that self-organizing agent populations are the most successful, growing larger than populations employing different social organization paradigms. Specifically, self-organization is compared to egalitarian-like and static hierarchical organization models. The success of this social organization 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 [9,24]. Moreover, we analyze the effects of the concept of "power distance" on self-organization in this society.

The rest of this paper is structured as follows: Sect. 2 below provides a review of the existing literature on ABM and MAS applied in archaeology. Section 3 presents our multiagent model, by describing its environmental representation, the agents and their interactions, and their various social organization-related characteristics. Following that, Sect. 4 describes the *self-organization* framework incorporated in this work; and presents an appropriate evaluation mechanism that measures the utility for agent re-organization decisions. Section 5 then presents our specific case study of early Minoan societies, and records the empirical evaluation of our approach, by first detailing the comparison methods and the simulation parameters for the various scenarios considered, and then analysing the obtained results. Finally, Sect. 6 concludes this work, and discusses future research directions.

2 Background and related work

In this section we provide some background on important concepts and approaches relevant to our work. Specifically, we discuss the question of understanding the social organization of a given society, as viewed in archaeology and MAS research; and provide a brief review of existing ABMs used to aid archaeological research.

[3] A sketch of this model appeared in a short AAMAS-2014 paper [10].

2.1 Social organization through the prism of Archaeology

Social Archaeology [54] seeks to understand the social organization of past societies at many different points in time. To this purpose, it has strived to define the right questions to ask, and to devise the means of answering them. It is only natural that different kinds of society raise different kinds of meaningful questions. For instance, a mobile group of hunter–gatherers is unlikely to have exhibited a complex centralized organization. Thus, in order to determine the way many aspects of a societal organization behaves in practice, one needs a frame of reference—a plausible classification of societies against which to test hypotheses and ideas.

A society classification system that has found much support in archaeology was the one proposed by E. R. Service [54,59]: *Bands*, small-scale societies of hunters and gatherers, less than 100 people, who move seasonally to exploit resources and lack formal leadership so that there are no marked economic differences in status among their members. *Segmentary societies* are larger than bands, but rarely number more than a few thousand. Their diet or subsistence is based on cultivated plants and domesticated animals and are typically settled farmers or nomad pastoralists with a mobile economy (which exploits resources in an intensive manner). *Chiefdoms*, on the other hand, operate on the principle of ranking and difference in social status between their members. There are lineages, graded on a scale of prestige, and the society governed by a chief; there is no true stratification into classes, however. A chiefdom generally has a center of power and may vary in size. *Early states*, finally, preserve many of the features of chiefdoms but the ruler has the explicit authority to establish laws and enforce them by the use of a standing army. The society is stratified into different classes and is viewed as a territory owned by the ruling lineage, and populated by tenants who have the obligation of paying taxes and tolls, developing a complex *re-distributive system*. Such societies often exhibit a pronounced settlement hierarchy.

The classification system above can admit a given society into more than one category. Moreover, it is far from clear that one should assume societies inevitably evolve from bands to segmentary societies, or from chiefdoms to states [54]. Earle and Johnson [40] chose a more evolutionary typology, based on social and political organization, where the mobilization and exchange of goods and services between "families" and the interconnected processes of technological change and population growth drive social change and transformation of human societies over time. Lull and Mico [47], on the other hand, review political philosophies from Greek antiquity to contemporary evolutionism, and offer an alternative classification system based on historical materialism. In any case, there are sufficiently marked differences between simple and more complex societies, as increased specialization and intensification takes place among different aspects of their culture.

Social archaeology asks a great number of additional questions regarding the nature and internal organization of the society under study. For instance, are the main social units, individuals or groups, forming it on a more-or-less equal base, or do prominent differences in status, rank, prestige within the society, or perhaps even different social classes exist? A number of important characteristic features that different kind of societies exhibit have been described by existing research, but many more are yet to be discovered [54,59]. There are many methods for acquiring information regarding the internal social organization of an early society. Beyond field survey—which aims to discover mainly a presumed hierarchy of a settlement—making use of settlement pattern information, written records, oral tradition and approaches from ethno-archaeology are included as well [54]. Clearly, the variety of methods used and the inherent uncertainty of the domain gives rise to a rich space of hypotheses for any given question regarding the social organization of early societies. This is where multiagent systems research can potentially offer a helping hand.

2.2 Social organization through the prism of multiagent systems

Multiagent system approaches towards organizational design can be considered to be either agent-centric or organization-centric [46]. In organization-centric approaches, the focus of design is the organization which has some rules or norms which the agents must follow. Thus, the organizational characteristics are imposed on the agents. The former focus on the social characteristics of agents like joint intentions, social commitment, collective goals and so on. Therefore, the organization is a result of the social behaviour of the agents and is not created explicitly by the designer. While a lot of *re-organization* framework models have been proposed in the MAS community (Opera [18], OMNI [62], Norms based [48], ODML [33], KB-OR [60]), such reorganization methods need to be provided with a particular set of requirements to produce an agent organization suitable for the respective problem solving process; agents are not permitted to modify their organizational characteristics that have been pre-designed, or do not allow flexibility in the interactions. In the work of Dignum et al. [19], re-organization issues in agent societies are discussed, such as how and why organizations change, and how can reorganization be done dynamically, with minimal interference from the system designer. As argued there, one of the main reasons for having organizations, is to achieve stability. However, environmental changes and natural system evolution (e.g. population changes), require the adaptation of organizational structures. Thus, *re-organization* may be the answer to changes in an artificial environment of agent societies, if it leads to increased capacity for survival (vitality) or power to live and grow (energy or utility); the reorganized instance should perform better in some sense than the original situation, not only for the organization but for the agent itself, given the assumption and essential characteristic of agent autonomy in multiagent systems or models.

The concept of *self-organization* can be considered as a specific instance of the agent systems re-organization notion. It is inspired by the spontaneous re-organization observed in natural systems functioning without any external control, and has subsequently successfully been applied in MAS research [17]. Such mechanisms 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 MAS. Intuitively, in social self-organization methods like the one in the work of Kota [44,45], 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, predictably, almost a necessity in the face of uncertainty and ever-present change [19]. 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. In Sect. 4 we will present in detail a self-organization method developed for our work here, one which adopts aspects of and builds on the approach of Kota mentioned above.

2.3 Agent-based models of ancient societies

In recent decades, archaeologists have used computer and agent-based models to test possible explanations for the rise and fall of simple or complex ancient societies. One example of such a system is the study 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 [43]. The model results show the importance of environmental factors related to water availability for these settlement changes. However, the results for 30 different (parameterisation) scenarios of one run each are presented. Moreover, as in most of the existing models, agents actions in the model are mainly cultivation or farming and migration, not based on utility maximisation but rather on threshold rules. Finally, agents do not interact with each other but act independently.[4]

A similar (quite well-known) ABM study involved the cause of the collapse of the Anasazi, around 1300 CE in Arizona, USA [4,16]. Scholars have argued for both a social and an environmental cause (drought) for the collapse of this society. Simulating individual decisions of household agents on a very detailed landscape of physical conditions of the local environment, Dean et al. [16] indeed confirm the hypothesis that environmental factors alone cannot account for the collapse. Agents in the Anasazi model (of the same environmental area with the work of Kohler et al. [43]), however, once again do not interact with each other. Agents are *simple reactive* (i.e., incorporate simple condition-action rules [56]), and their actions mirror a rather nomadic style of social organization, instead of the more complex one that the Anasazi actually evolved until they abandoned the region around 1300 CE [25]. A further cause of concern regarding the model's accuracy and fairness is that Axtel et al. [4] apparently calibrated the model by minimizing the difference between the simulated and historical data, using only 15 simulations, and published the best fit, notwithstanding the apparent great variation in their results [36].

The study of the long-term dynamics of human society and in particular the spontaneous transition from a relatively simple hunter–gatherer society to one with a more complex structure has been also tried in the past [20]. The aim of this social simulation system—*Evolution of organized Society (EOS) project*—was to investigate the causes of the emergence of social complexity in Upper Palaeolithic France. Each agent is endowed with a symbolic representation of its environment, its beliefs, about other agents (the social model) or about resources in the environment (the resource model). An agent also has a set of *cognitive rules*, which map old beliefs to new ones. To decide what action to perform, agents have action rules which map beliefs to actions. Agents inhabit a simulated two-dimensional environment (grid of cells) and have associated *skills*. The idea is that an agent will attempt to obtain resources situated in the environment that come in different types, and only agents of certain types are able to obtain certain resources. The basic form of social structure that emerges, does so because certain resources have a *skill profile* associated with them. This profile defines, for every type of capability that agents may possess, how many agents with this skill are required to obtain the resource. A number of social phenomena were observed in running the EOS model, as for example "overcrowding" or "clobbering", when too many agents attempt to obtain resources in the same locale. However, agents in the model are autonomous only in the sense of *simple reactive* agents. Neither learning/adaptation nor a "utility" function of the agent's state or actions is introduced. Agents in the EOS model are rather *forced* by rules to change their independent state in favour of a recursive development of a hierarchical structuring of agent groups. Moreover, the authors mention that there are more than 60 rules

[4] Mortality and fertility rates in [43] depend on age, rather than on production.

including both cognitive and action rules, while none of them is described; at least for the cognitive part of the agents, there is no reference on the *internal* information processing of the agent, including tasks like reasoning, planning or problem solving. In order to study the transition from a simple societal organization to a more complex structure (without adding any bias), simulations should exhibit the emergence of such a phenomenon, rather than introducing it to the model a priori. In addition, while population dynamics is an important consideration for the accuracy and fairness of any ABM modeling a given society [14], this is not mentioned at all in the work of Doran et al. [20].

Archaeologists are now beginning to make use of spatial information in their models, through data provided by Geographical Information Systems (GIS). Models like the *Cyb-Erosion* framework overcomes the limitation of existing *landform evolution models* which use an agent-based approach to simulate the dynamic interactions of people with their landscapes but have typically failed to include human actions, or have done so only in a static, scenario-based way [64]. The interactions it simulates relate to a few main processes of food acquisition (hunting, gathering and basic agriculture) in prehistoric communities. Simulations demonstrate the value of this approach in supporting the vulnerability of landform evolution to anthropic pressure, and the limitations of existing models that ignore human and animal agency, and which are likely to produce results that are both quantitatively and qualitatively different. Although the ABM's goal-based agents do not interact with each other they can decide at each time-step what action to select (hunt, forage, collect firewood, other activities) based on their stored energy and the remaining daylight length.

The *Mason–Smithsonian Joint Project* on Inner Asia [12] is a complex social simulation project aimed at developing a better interdisciplinary scientific understanding of the rise and fall of polities—national territorial societies with their own system of government—over a very long time period, in order to examine the social effects of climate and environmental change. A next model of this project is the Mason Hierarchies model, developed by adding social and natural features to the simulation. Hierarchies rather than "households" agents are now present for modeling the explicit emergence of political entities in the socio-natural landscape. The model-building is based on the "canonical theory of social complexity" which is formally derived from the authors' general theory of political uncertainty rather than on a representative MAS or ABM architectural framework.

ENKIMDU [11] is a celebrated societal modeling framework. Since its conception, it has been employed in several "spin-off" projects, due to its ability to create a virtual world on which to run simulations based on environmental and social parameters. The original *ENKIMDU* work focused on the study of the Bronze Age Mesopotamian settlement system dynamics. The system can represent settlement populations that are demographically and socially plausible, and detailed models of social mechanisms that can produce and maintain realistic textures of social structure and dynamics over time. Agent decisions are influenced by natural and social circumstances such as low crop yields, endogamous or exogamous marriage patterns, and rates of death. As such, agent autonomy is somewhat limited.

MayaSim [31] is a very recent example of a simulation model integrating an agent-based, cellular automata, and network model of the ancient Maya social–ecological system. The purpose of the model is to better understand the complex dynamics of social–ecological systems, and to test quantitative indicators of resilience as predictors of system sustainability or decline. The ancient Maya civilization is presented as an example. The model examines the relationship between population growth, agricultural production, pressure on ecosystem services, forest succession, value of trade, and the stability of trade networks. These combine to allow agents representing *Maya settlements* (rather than households), to develop and expand within a landscape that changes under climate variation and anthropogenic pressure.

MayaSim agents are utility-based in the sense that they estimate the utility of the various actions at hand. However, they choose actions whose utility has reached some thresholds that are in fact hard-coded by the modeller. For instance, decisions on migrating or adding new and degrading existing trade route links between the agents, are based on threshold rules. Specifically, settlement agents may migrate when population levels decrease below a certain threshold required to maintain subsistence agriculture, while their utility function combines weighted functions for agriculture, ecosystem services, and trade benefit. The later is affected by agent resource exchange that occur between settlement agents since they are connected via a network of links that represent trade routes. It is assumed that when an agent reaches (or drops below) a certain size, it will add routes (or allow routes to degrade) to agents in nearby cells within a Moore neighbourhood (spatial ties). A larger network produces greater trade benefits, and also the more central an agent is within the network (centrality), the greater the trade benefits for that individual agent. The model was able to reproduce spatial patterns and timelines somewhat analogous to that of the ancient Maya, although this proof of concept stage model requires refinement and further archaeological data for better calibrations; and although the temporal extent is only a few hundred time steps, each representing roughly 2 years.

The second model we are aware of that can be considered utility-based, even though the author does not use the term utility explicitly, is the one proposed by Janssen [37] for understanding how prehistoric societies adapted to the American southwest landscape of their era. The ABM could explore to some extent how various assumptions concerning social processes affect the population aggregation and size, and the dispersion of settlements. Agent interactions in that simple model, however, are largely determined by rules that are built in the system. Our model in this paper shares several basic features with that of Janssen, but is also in many ways distinct from that model, as we will be detailing in Sect. 3.6.

In summary, ABM and MAS nowdays can integrate geospatial information with archaeological evidence and theories, and help researchers gain a better understanding of ancient social organization and environmental processes. However, as mentioned earlier, most of existing models do not define agents in the way these are defined in the MAS community, perhaps because domain experts in social sciences do not define such models in computational terms. Thus, essential agent features such as *autonomy* or *interaction capability* are considered as “metaphors” in the design level only, and do not appear in the actual system implementation. Social scientists and archaeologists are interested in understanding human societies, in particular the mechanisms that allow these systems to self-regulate, and in the processes that shape and modify rules of behaviour. To aid them in this endeavour, computer scientists have to build ABMs that are flexible and open; agent behaviours should be allowed to evolve over time, rather than being pre-determined at design-time. This does not imply that the ABMs need to be highly complex; rather, it implies a need to develop and study system-regulating mechanisms that are actually *emergent* from some form of evolution and self-organization of the underlying agent society. The model that we will now present is such an open one, and can incorporate self-organization mechanisms that allow for flexible agent interactions and the dynamic modification of organizational characteristics.

3 A utility-based multiagent model for artificial ancient societies

In this work we have developed a functional ABM system prototype for simulating an artificial ancient society of agents evolving in a 2D grid environmental topology. The grid is also equipped with attribute fields that register information regarding the availability of water, elevation, and slope. The agents correspond to *households*, which are considered to be the main social unit of production for the period [65], each containing up to a maximum number of *individuals* (household inhabitants). 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 number of those "fields" depends on the agent household size, as we explain further below.

The model then determines how the agent society evolves as follows. At every time step corresponding to a period of *1 year*, agents (i.e. households) first harvest resources located in nearby cells (corresponding to the fields they are cultivating). They then 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 behaviour in effect), or they might even eventually consider moving to another location or settlement. When the *self-organization* social paradigm is in use, agents within a settlement continuously re-assess their relations with others, and this affects the way resources are ultimately distributed among the community members, leading to "social mobility" in their relations.

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. An abstract overview scheme of the dynamics between the main model elements is presented in Fig. 1. The arrows in the figure show how one element affects another in the MAS simulation model.

The ABM allows us to explore the use of various technologies that could potentially be used by the agent society, and thus test their impact on population size and dispersion (e.g., on the civilization's viability). In our work, it allows the use of two agricultural technologies: *intensive farming* ("garden" cultivation with hand tillage, manuring, weeding, and watering) and *extensive cultivation* (large-scale tillage by ox-drawn ards).[5] Additionally, the ABM attempts to assess the influence of different *social organization paradigms* on population growth and settlement societies distribution. Importantly, the model allows us to evaluate the social paradigm of agents *self-organizing* into an implicit stratified social structure, and continuously re-adapting the emergent structure, if required.

3.1 Model environment and resources

Agents and resources in the multiagent model are located within a 20×25 km area with a 100×100 m cell size for the grid space. Thus, the landscape consists 50 K cells, while the time slot investigated is ≈2000 years (ca. 3100–1100 BCE), with annual time steps. The environment has also various data layers (see Fig. 2) representing various aspects of the model landscape contributing indirectly in agent's *decision-making* process, like where to settle and/or cultivate. The input spatial information are derived from modern data and are concerning the *topography*, which is today's Digital Elevation Model (DEM), *slope* and *aquifer* locations (rivers and springs).

[5] These are the agricultural technologies in use at the period of interest for our case study [27,35].

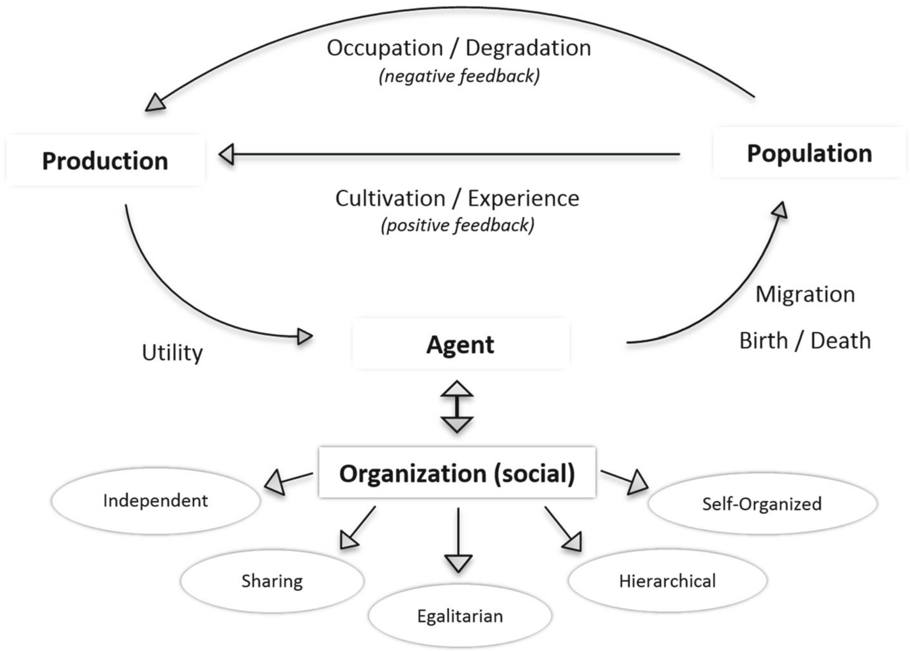


Fig. 1 Multiagent model overview

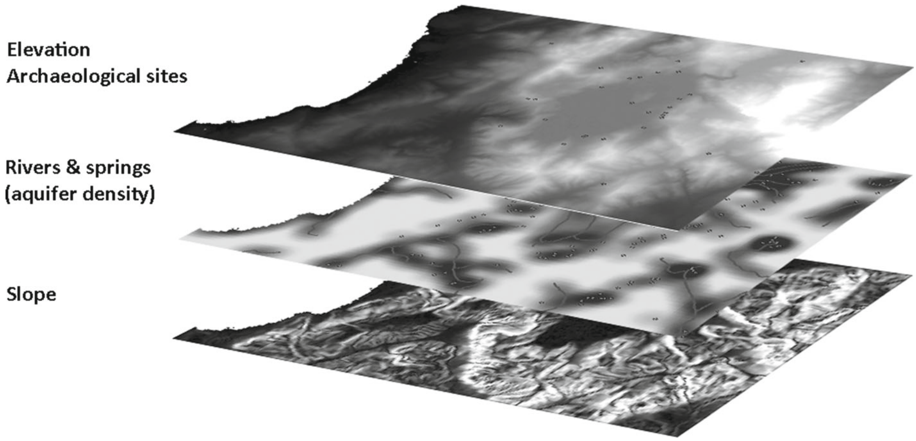
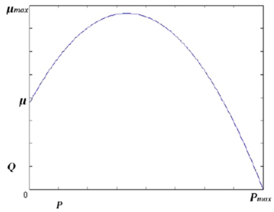


Fig. 2 Environmental data layers of the multiagent model

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 a given cell, there is an increase in cell farming output (as agents get better in working the land and harvesting their crops). On the other hand, the more a cell is used, the more its "soil quality" is reduced (due to various erosion processes). Thus, the rate of soil depletion depends on the settlement population size: a higher population puts more anthropic pressure on the land.

To model these dependencies, we devised a function R_i to describe the *agricultural production quantity* or *reward* associated with cultivating a land cell i:

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



where P is the current *population size* of the corresponding settlement (i.e., number of individuals residing in the settlement, not the number of household agents),[6] 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 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° (this is actually a generous assumption, especially considering the era being modelled). Thus, α_i is used to represent the decay of agricultural land suitability with increasing slope.

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, the discrete version of the logistic differential equation, widely used to model population growth [63]. In our simulations, a cell's production output R_i at a given run (corresponding to period of 2000 years) is multiplied with a sample from a standard normal distribution, and thus varies across runs.

3.2 Agents and their actions

Households are *utility-based autonomous* agents who can settle (or occasionally re-settle) and cultivate in a specific environmental location. They also possess an explicit representation of the environmental grid (migration radius), and use this to choose the best available migration location they can move to, in order to improve their utility. Thus, the actual agent architecture is a hybrid one, combining properties from a reactive and a deliberative agent architecture, but they can eventually be classified as utility-based agents, since they seek to maximise the expected value of a given utility function via their actions (e.g., choosing a migration location, or asking others for help).

In particular, agents *optimize* their decisions with respect to the (long-term) *value* of being at a given state (corresponding, e.g., to being at a particular location while possessing a specific amount of stored resources, and so on). This value is provided, as is standard in decision theory, by a state and action-dependent *value function* [50,51]. We begin our

[6] In Eq. 1 we let the agents organization population P influence the amount of labour applied on a cell, even though any given cell contributes to the utility of a single agent only (cf. Eq. 3), since field cultivation was in many respects communal in those times [61]. Regardless of that assumption's validity, this value is essentially normalized by the maximum possible population; thus the R_i function's desired behaviour would have been entirely similar had we used the household size instead of the settlement population.

description of agent decision-making deliberations in this paper, however, by assuming that an agent takes decisions by considering only the outcomes of its immediate actions, which are relevant to its current state only. Thus, there is no need to include the state as a parameter of the value function. Therefore, though we will explicitly consider states in Sect. 5.2.4, for now we simply let $U_x(b)$ denote a function describing the immediate value of some action b to agent x. Then, at every time step, x picks the best action b' in the set of actions $Actions_x$ at its disposal:

$$b' = argmax_{b \in Actions_x} U_x(b) \tag{2}$$

The main preoccupation of the agents is to *stay alive* by acquiring and consuming resources. If an agent fails to acquire enough energy it will eventually die out, since it will stop procreating, as explained in Sect. 3.3 below. Acquiring energy is the only inbuilt goal of the agents. In the case study considered in the current paper, agents acquire energy only via harvesting the lands. This can be done (*a*) either at the agent's current location (via employing the *cultivation* action described below); or (*b*) at some other location to which the agent migrates (cf. *migration* action below). Therefore, since there are only two actions to consider, the (expected) utility U_x of the agent x can be simply described as follows (assuming the agent cultivates n environmental cells):

$$U_x = \max \left\{ \sum_{k=1}^{n} R_k, U'_x \right\} \tag{3}$$

Equation 3 thus determines that the utility of agent x depends on the expected agricultural production of the cells it cultivates (its total harvested resource amount), as well as the expected utility U'_x of a new candidate migrate location, which in turn depends on the agricultural production quality of the new position (immediately after migration). The number of cells n that a given agent x needs to (and is able) to cultivate at a given position, depends on the number of its (household) individuals, and the agricultural technology in use, as we detail below. Notice however that, as described in Eq. 3 the utility function is rather myopic, taking into account as it does only the *immediate* reward R from cultivating a specific location (either the current one, or the one the agent migrates to). Nevertheless, Eq. 3 can be readily extended to incorporate the *long-term quality* of agent decisions. To illustrate this fact, in Sect. 5.2.4 we describe how to determine the value of non-myopic, long-term settlement or migration policies via the use of Markov Decision Processes (MDPs) [50].

Now, an agent x needs to be receiving some minimum utility from its cultivated cells, in order to be fit enough to procreate (see Sect. 3.3). This minimum utility (minimum level of resources) for household agent x containing j individuals is calculated as:

$$u_x^{thres} = j \times res_{min} \tag{4}$$

with res_{min} being the *minimum amount of resources* (in kg) required by an individual per year. The value of the res_{min} can be set based on archaeological research estimating the average yearly food consumption per person during the era in question.

As mentioned, agents employ actions by which they may interact with the environment. We term these *agent-environment* actions, to distinguish them from the actions that agents may use to interact with other agents in the environment. The currently implemented primary (*agent-environment*) actions include land cultivation and migration to another location, if an agent's current location does not fulfil the agent demands:

Action: Cultivation An agent may cultivate the land within a specified range from its settled location, and is able to store any *surplus* resources in its *storage*, for up to

yrs years. The number of cells a household cultivates depends on its size, and the output of the agricultural technology currently in use (cf. Sect. 3.4 below). The agents are assumed to be "settled farmers" who, however, do not aim to expand their farming territory more than what they require it to be in order to be able to sustain themselves. This is because during that era farming activities relied mainly or entirely on human labour, thus entailing a high cost, and ease of access to the cultivated lands had to be taken into account [35]. Thus, agents in our work, decide, on a yearly basis, to cultivate only the number of cells deemed necessary in order to sustain themselves for another year. A farming area thus contains a number of cells $n = number\ of\ household\ inhabitants \times res_{min}(\text{kg})/(maximum)\ harvest\ amount\ provided\ by\ the\ agricultural\ regime\ in\ use\ (kg/ha)$. Moreover, 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 yrs years in a row ($U_x < u_x^{thres}$) and the storage is empty ($storage = 0$), it considers migrating to another location or settlement.

Action: Migration An agent moves to another location only when it finds a location within a radius r_{max} that is *better* than its own location. At time step t, the agent calculates its expected utility U_x' for the new location at time step $t + 1$, as the average *agricultural production* of the neighbouring cells which is defined by Eq. 1, considering the agent moved to the respective *unused* cell (i.e., a cell that 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 expected utility U_x' of the agent for the new location is higher than the agent's current utility U_x, the location is considered to be an option for migration. If there are many such locations, the agent migrates to the one perceived to be the most favourable; considering the small modeling landscape area, agent's *migration radius* was set to full environmental view with negligible resettlement cost (see Sect. 5.1).

Apart from the aforementioned actions, yet another *agent-environment* interaction that is *not*, however, under the direct control of the agent, is that of *hatching*—i.e., generating offspring. Hatching does have an impact on the agent utility (since this is affected by the overall population, via Eq. 1), but the agent can only affect its probability of generating offspring by making sure that it is accumulating enough utility via the rest of its actions. Hatching takes place once a year (per agent), with some probability, which corresponds to an agent-specific *population growth rate* (cf. Sect. 3.3) below. Whenever 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 so doing, 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. The maximum number of agents per cell is derived by the maximum number of individuals per cell, as well as the maximum number of individuals per household. These parameters are set using existing archaeological estimates.

3.3 Population dynamics

The total number of agents in the system changes over time, as *individuals* belonging to households are born or die. The *death rate*[7] for an individual belonging to a household is given by a variable r_{death}, whose value in our "case study" simulations was set to 0.002;

[7] Certainly, however, when a household agent's utility and storage values reach zero, all individuals in the household inevitably "die", and the agent is removed from the system (and organization).

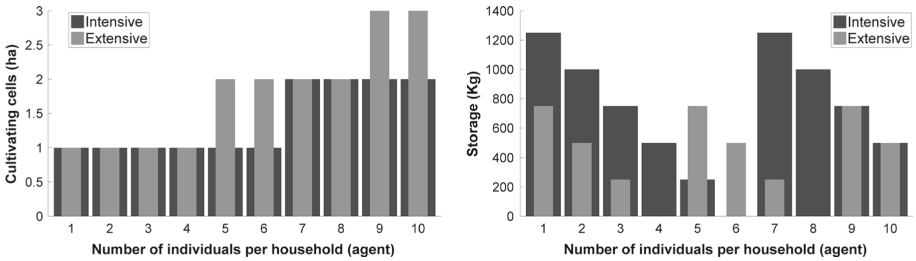


Fig. 3 Number of cultivating cells (*left*) and *maximum expected* resources in storage (*right*) for a household agent *wrt.* intensive and extensive agricultural technology

while the agent procreation ability (determining the annual levels of births) is based on the amount of energy consumed by the household agent during the year. Specifically, the *birth rate* is defined to be:

$$r_{birth} * \hat{U}_x / u_x^{thres}$$

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

$$\hat{U}_x = \min\{U_x, u_x^{thres}\}$$

As such, $\hat{U}_x / u_x^{thres}$ is at most 1, and the agent-specific *birth rate* is at most r_{birth}. However, whenever $U_x < u_x^{thres}$, the agent attempts to "replenish" U_x by acquiring energy by its storage (or, if the self-organization social behaviour is in use, maybe by acquiring energy from other agents). These rates, given the specific r_{death} and r_{birth} values used in our simulations, produce a *population growth rate* (= birth rate − death rate) of $0.001 = 0.1\,\%$, when households consume adequate resources (*i.e.*, when they acquire utility equal to u_x^{thres} or more). This corresponds to estimated world-wide population growth rates during the Bronze Age according to Cowgill [14].[8]

3.4 Technologies

Our model can be readily incorporate any ancient technologies that the agents might have had access to, depending on the era and location being modeled. Currently, the technologies implemented correspond to two distinct (Early) Bronze Age agricultural regimes [27,42]:

Intensive agriculture, where agents cultivate intensively the neighbouring land area, leading to greater production per hectare.

Extensive agriculture where agents can expand their cultivated areas, using more land, but producing less per hectare when compared to the *intensive* agricultural practice.

The output associated with *intensive agriculture* in our model is 1500 kg/ha, while the production associated with *extensive agriculture* is 1000 kg/ha. These values are appropriate estimates for these two regimes, given the period modelled [35]. Then, the number of candidate cultivation (or field) cells and the expected maximum energy stored for any agent in the model, depending on the agricultural regime in use, is shown in Fig. 3.

One example of how these two different technologies are used by the agents is the following. A household agent x with five individuals ($j = 5$), needs to accumulate $u_x^{thres} = 5 \times 250 = 1250$ kg of resources for the year, assuming $res_{min} = 250$ kg (cf.

[8] Others estimate growth rates in mainland Greece and the Aegean to be between 0.1 and 0.4 % per year, for long periods during the Neolithic Era and the Bronze Age [2,41].

Eq. 4). If agent x adopts an *intensive* agricultural strategy (producing $\mu_{max} = 1500$ kg/cell), it chooses *one* (unoccupied) nearby cell ($1 \times 1500 = 1500$ kg) from its settled location for cultivation, since that much is enough for sustaining its individuals for the current year ($u_x^{thres} < 1500$). On the other hand, if agent x adopts an *extensive* agricultural strategy (assuming that produces $\mu_{max} = 1000$ kg/cell), it chooses *two* (unoccupied) nearby cells ($2 \times 1000 = 2000$ kg) from its settled location for cultivation, since one cell is not enough for sustaining its individuals for the current year ($< u_x^{thres}$), thus expanding its farmland.

3.5 Social organization paradigms

Agents also have actions by which they interact with each other. These *agent-agent* actions correspond to distinct *social*[9] *organization paradigms*, determining the way by which distribution of resources takes place among the population. In our work, we examine five different social organization paradigms ("behavioural modes" or "resource distribution schemes"): *independent*, *sharing*, *egalitarian*, *hierarchical* and *self-organized*; by so doing, we shed some light on crucial aspects of the ancient societal organization, and the relation between crop yield, resource allocation patterns, and the reproduction and legitimization of authority. In more detail, the aforementioned paradigms are the following:

Independent Agents acquire (harvest) and consume resources independently. Although there is no distribution of harvest among the agents, the actions (e.g., cultivation or migration) of the various agents have an impact to the welfare of others—the overall welfare of the settlement (cf. Eqs. 1, 3).

Sharing Agents distribute energy amounts (produce) within a settlement based on reciprocity. All stored and newly harvested resources are pooled each year, and distributed equally among the agents—that is, resources are distributed *equally* among the *households* in the community. This social paradigm is quite interesting, as it effectively allows the creation of "poorer" or "wealthier" households, since agents with fewer individuals gain a survival advantage, albeit a temporary one: they end up getting comparatively more resources due to the distribution scheme, and can thus better sustain themselves throughout the next year—but this is an advantage they will lose if their household size increases.

Egalitarian In this scheme, storage and harvest is pooled each year and distributed among the agents, but now *resource distribution is proportional to their household size*—i.e., it is proportional to the number of the actual individuals in each household. Therefore, this paradigm mirrors a truly egalitarian society, and no agent gains an advantage because of the resource distribution scheme.

Self-organized Agents autonomously re-arrange their relations, and hence the underlying social network structure describing these relations, without any external control. They do so in order to adapt to changes in requirements and environmental conditions. In other words, they *constantly re-evaluate* and *possibly alter* their *relations* or *links* with other agents. These relations determine the way resources are ultimately distributed among the agents. In Sect. 4, we provide a detailed description of this social organization paradigm.

(Static) Hierarchical Agents distribute resources based on a *fixed hierarchical social structure*. The agents are linked to each other via static social relations, which determine the amount of produce each agent acquires via the distribution scheme. The determination of the

[9] More accurately: *socio-economic*.

original relations, and the actual resource distribution takes place following the same rules as those governing the self-organized social organization paradigm (described in Sect. 4).

3.6 Relation to existing models

Our model in this paper was originally inspired by that of Janssen [37], and thus shares several basic features with that model. Just like [37], we also model population dynamics, as a model should do—but via an entirely different population growth function. Our agents also correspond to households, and they use a similar process to the one described in [37] for deciding whether to migrate or not. Apart from these similarities, the models are different in all other aspects.

To begin with, no individual members are actually introduced in that model as components of the household agents. By contrast, individual household members are present and key in our model, since (*a*) their number affects the estimated agricultural production (via Eq. 1), and (*b*) for certain social organization models, they play a crucial role in determining how the accumulated resources are to be dispersed among the agents (cf., the "egalitarian" organization model described in our work). Second, the modeling area in [37] is not an actual landscape, but a flat 20×20 grid (an arrangement which, of course, speeds up the simulations); while agents cultivate just one cell, the one the agent is currently settling, or the one it is migrating to where renewable resources can be found (after the agents have consumed/exhausted harvested). Another notable difference between the two models, is that ours can (and does) incorporate different technologies—our agents use either intensive or extensive farming techniques, instead of cultivating just one cell.

Moreover, in [37] the production/harvest yield is exactly the same for each agent within a settlement (same cell), thus potentially violating maximum resource levels of the occupied cell. Production and thus agent utility is essentially affected only by resource regeneration rates defined, and the agents make no attempt for active utility maximization, apart from considering migration when resources at the current cell are exhausted. Indeed, the main action of an agent appears to be "migration" rather than cultivation (or at least the use of this action is rather pronounced in the simulation results), as the reported agent migrations number is proportional to population size. This corresponds better to a nomadic hunter–gatherer society, rather than one of "settled farmers" (notwithstanding the fact that [37] is modeling a settled farmers society). By contrast, agents in our model take utility-based decisions, at every time step, regarding the appropriate number of cells to cultivate, given the number of their individuals and the agricultural strategy employed, or by migrating to another location or settlement for farming purposes, if such an option is deemed beneficial in terms of expected cultivation yield.

In addition, [37] estimates the utility-affecting expected agricultural production given estimated rainfall, for the same period simulated in [4,16,43]. The rainfall estimates are reconstructed using modern-day annual data obtained via the Palmer Drought Severity Index (PDSI). By contrast, there is no climatic reconstruction in our model, and thus the annual resource production (cf. Sect. 3.1) does not depend on the accuracy of any such method.

As a final note, the viability of an independent and an egalitarian-like social organization model was examined in [37]. Interestingly, there was no observed statistically significant difference among them, as the author notes. Our results, by contrast, indicate that there is in fact a visible difference among these social organization paradigms. Of course, as outlined in the text, many components and component parameters in our model are entirely different to those of [37], and they are also instantiated on different modeling areas and historical places/times, thus this discrepancy might not be surprising.

4 Self-organization

The rise of complex 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 Middle Minoan period marks a transition from an egalitarian to a more complex, state-like society with a clear hierarchical structure crowned by a central, administrative authority [9]. There is also a belief that stratification in Minoan Crete precedes the appearance of the palaces by several centuries [7,24]. In our work here, we examine whether the adoption of a self-organized agent organization (settlement) can indeed give rise to a *dynamically stratified social structure* that is be able to sustain itself through time.

As mentioned in Sect. 2, the work of Kota [44] on "self-organizing agent organizations" is an example of a recent *decentralized structural adaptation* mechanism originating in the multiagent systems community. In that work, an abstract agent organization framework for depicting distributed computing systems is introduced, along with a task environment representation model and a suitable performance evaluation system. The organization consists of agents providing services and having computational capacities. The structure of the organization manifests the relations between the agents, and regulates their interactions. Crucially, the proposed self-organization (structural adaptation) process is applied individually and locally by all the agents, in order to improve the organization's performance.

Our self-organization model here is inspired by the work of Kota. However, we modify that model in several important ways, as described in detail in Sect. 4.2 below. In effect, and in distinction from Kota's approach, the self-organization technique presented here is one that results to the continuous *targeted redistribution of wealth* (i.e., energy resources, so that resources flow from the more wealthy agents to those more in need within the organization), maintaining a dynamically stratified social structure. This will become clear below.

4.1 Relations and interactions

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 resources. A shortage in resource 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*. Agents perform three types of self-organization actions: (i) *execution*, (ii) *allocation*, and (iii) *adaptation*.

As mentioned, *task execution* involves the accumulation of produce to cover a perceived deficit. An agent x may *execute* a task (by consuming energy from its storage), or *re-allocate* the task (if its *storage* $= 0$) to another capable agent y; and executes it otherwise. Task execution then means that agent y delivers to x some resource by taking that amount out of its own storage. If agent y is only able to replenish a portion of the requested produce allocation task, this is considered a *subtask execution*. Note that capable agents in our model (i.e., those with *storage* > 0) related to agent x, always accept produce allocation or execution tasks. This is due to an assumption of high degree of cooperation (sharing) among households in Greece before the Middle Bronze Age [29]. Thereafter, agents reorganize and *adapt* their relations, maintaining a dynamic stratified social structure. We will expand on the adaptation process in the next subsection.

Interactions between agents are therefore regulated by the settlement's social structure. Relations among agents are classified into three types (i) *acquaintance* (aware of the presence, but having no interaction), (ii) *peer* (low frequency of interaction); and (iii) *authority* (a *superior—subordinate* relation, where agents have a higher frequency of interaction). The authority relation depicts "superior status" of an agent over the subordinate agent in the context of their social organization, i.e. higher produce transfer amounts are possible than the subordinate agent. The peer relation will be present between agents who are considered more-or-less equal in status (i.e energy transfer amounts) with respect to each other and is useful to expand vertically the assumed *stratified* social graph. When two agents are not linked to each other by a relation like acquaintance, peer or authority, they are considered to be strangers to each other (belong to another organization or settlement). Note that when the *hierarchical* social organization paradigm is in use, the same relation types exist, but they are static—that is, they do not change over time.

Whenever either the *hierarchical* and *self-organized* social organization model is in use, agents are able to create relations with other agents within a community based on the following rules: (*i*) when an agent migrates to another settlement creates an *authority* relation as a "subordinate" to the "superiors" of the settlement, and a *acquaintance* relation with the rest (however, when the *hierarchical* social behaviour is employed, due to the agents relations being static, a *peer* relation is formed with non-superior agents rather an *acquaintance* relation); and (*ii*) when an agent creates an "offspring" within the settlement , the new agent creates an *authority* relation in which it takes up the role of a "subordinate" to its "superior" parent agent, a *peer* relation with all its parent "subordinate" agents, and an *acquaintance* relation with the rest.

Moreover, the relations are mutual between the agents; that is, an existing relation between any two agents is respected by both. Therefore, during the social re-organization/ adaptation process we describe below, both concerned agents will have to agree on changing the relation.

4.2 Task execution and allocation, and social re-organization

Mirroring the work of Kota et al. [44,45], our self-organization algorithm has two main stages: the *task execution and re-allocation* mechanism, by which it is decided which agents will receive produce (energy resources) from others to cover their needs, based on their relations; and the *re-organization (decentralized structural adaptation)* one, used for re-evaluating and potentially altering their relations at every time step.

Let us start by describing the task execution and task allocation stage. The steps of this mechanism are as follows:

(i) When an agent needs to execute a task, i.e., when its current harvest is not enough to cover its needs,[10] it will allocate the task (or subtask) to itself if possible (*storage* > 0).
(ii) Otherwise, it will try to allocate the task to one of its capable *superiors*, i.e., those with *storage* > 0, choosing among such superiors randomly. The intuition here is that agents in need will be asking for help based on the related agent's *status* within the community.
(iii) If neither the agent itself nor its superiors are capable of executing the task, then the agent tries to reallocate it (the whole task or the remaining subtask) to one of its *peers*.
(iv) If none of its peers is capable of executing 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.

[10] We note that the notion of "lineages" for agent organization evolution has actually been implicitly introduced in the order by which agents in need are given priority for asking for help. Specifically, the "older" an agent (in need) is within the community, the higher in the energy distribution priority queue is placed. This is a social norm mirroring an indirect "kinship" or "tradition" system, in use within the artificial families.

(v) On the occasions when the agent does not have any superiors, and neither peers nor subordinates are capable of the task, it checks among its acquaintances for a capable agent, and tries to form a subordinate relation with an acquaintance agent.

In every assignment of a task to a capable agent, execution (offering of stored energy amount) takes place, and 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 resource exchanges among the agents, and these exchanges in turn lead to the dynamic creation of an implicit (and non-static) stratified social structure—through the social re-organization process we describe next.

To begin, every *produce allocation task* to a capable agent (i.e., every task execution action) has an associated load. The total *load* $l_{x,tot}$ added onto agent x by all other agents within the organization, is the sum of its resources that were given out to others in that time-step:

$$l_{x,tot} = \sum_{t \in T_x} res_t \tag{5}$$

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 settlement organization. In what follows, we denote by $l_{x,y}$ the load added onto agent x solely by assignments from y. Loads on the various agents are assumed to be known to everyone in the community.

Agents use the information about all their past and current year allocations to re-evaluate their relations with their subordinates, superiors, peers and acquaintances. This evaluation is performed during the reorganization stage, and is based on the overall load between a pair of agents, in case the relation had been different than the current one. An *authority* relation means that there is a relative difference in the amount of load per assigned tasks between them; a superior 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.

It is, therefore, easy to draw a connection between an agent's load and its perceived *social status*. An agent that is able to serve tasks with a high load value, that is, has enough stored food quantities to help others in need, should clearly be ranked higher in the social hierarchy. Intuitively, a high load difference between two agents indicate a difference in social status.

To sum up, the relation between every pair of agents x and y has to be in one of the following *relation states*: *acquaintance*, *peer* and *authority*. For each of these states, the possible re-organization actions available to an agent y are as follows:

1. when agent 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 agent 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 agent 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 them, where y is subordinate of x; and
   (iii) no_action.
4. when agent 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.

The above reorganization actions are either "atomic" (e.g., $form\_auth_{x,y}$) or "composite", involving the removal of a relation and its replacement by another (e.g., $rmv\_auth_{y,x} + form\_peer_{x,y}$). The composite actions are necessary as a pair agents cannot have multiple relations to each other simultaneously. The choice of a re-organization action is utility-based: actions are selected by the agents according to their utility—that is, the re-organization action with the higher utility value is executed. The utility of re-organization action a that modifies the relation between agents x and y at a given state, is evaluated by agent y via the use of an action evaluation function F with the general form:

$$F(a, x, y) = \pm rdLoad(x, y) \pm L \tag{6}$$

where $rdLoad_{x,y}$ is the *relative difference* between the load on x and y; and L, an adequate *limit ratio* (%) for this difference to be evaluated in order to estimate the expected utility for changing an existing relation. Intuitively, combined with L, the *relative difference* is used as a quantitative indicator of quality assurance and control, for the repeated evaluation of agent relations over time. The effects of the re-organization actions are deterministic, and result to state transitions, depicted in Fig. 4.

Table 1 lists the evaluation functions for the five atomic actions. In the case of the composite actions, the value is simply the sum of the individual evaluations of the comprising actions. As already mentioned, from all the possible re-organization actions available to agent y, the one chosen for execution is that with the higher utility value. We note that the re-organization action evaluation functions we use here are entirely distinct from those used in the work of Kota [44].

To elaborate further on how the action evaluation functions work, let us consider the following examples of their use, assuming $L = 60\,\%$. Agents x and y may form an *authority* relation as long as their relative "total" load difference is $>60\,\%$, thus allowing a positive output value $F > 0$ for re-organization action $form\_auth_{x,y}$. That is, $l_{x,tot}$ is much larger than $l_{y,tot}$. They may form a peer relation (action $form\_peer_{x,y}$) when their relative "total" load difference is less than $60\,\%$—i.e., they are of an approximately equal social status as $l_{x,tot}$ is approximately equal to $l_{y,tot}$, thus allowing a small output value be subtracted from L. In a similar manner, agents x and y may dissolve an *authority* relation as long as their relative current load difference allows an output value $F > 0$ for re-organization action $rmv\_auth_{x,y}$—i.e. $l_{x,y}$ is approximately equal to $l_{y,x}$ or $l_{y,x}$ is greater than $l_{x,y}$ (and thus there is no reason to believe that agent x is superior to y). Finally, the agents may dissolve a

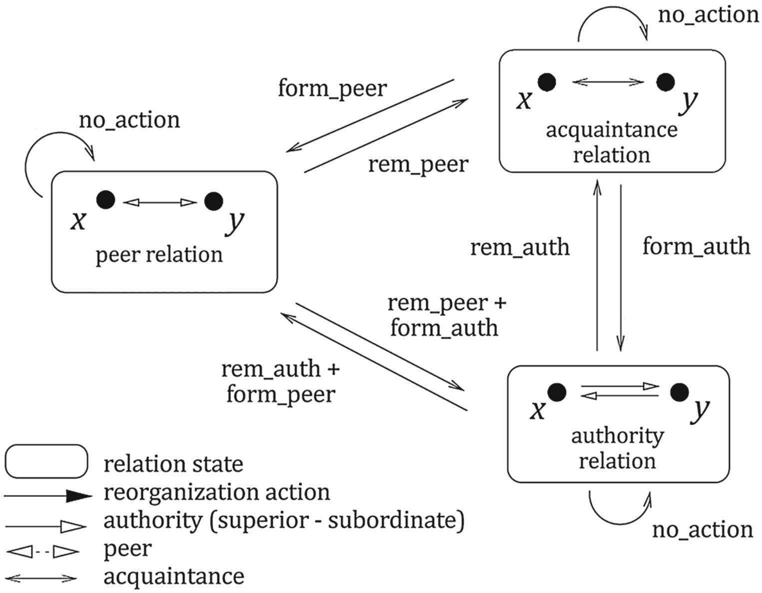


Fig. 4 Relations state transition

Table 1 Atomic reorganization actions, and corresponding action evaluation functions

Action (a)	Action evaluation function used
$form\_auth_{x,y}$	$F(a) = (l_{x,tot} - l_{y,tot})/\max\{l_{x,tot}, l_{y,tot}\} - L$
$rmv\_auth_{x,y}$	$F(a) = -(l_{x,y} - l_{y,x})/\max\{l_{x,y}, l_{y,x}\} + L$
$form\_peer_{x,y}$	$F(a) = -\lvert l_{x,tot} - l_{y,tot}\rvert/\max\{l_{x,tot}, l_{y,tot}\} + L$
$rmv\_peer_{x,y}$	$F(a) = \lvert l_{x,y} - l_{y,x}\rvert/\max\{l_{x,y}, l_{y,x}\} - L$
no_action	$F(a) = 0$

peer relation (action $rmv\_peer_{x,y}$) when their relative current load difference is more than 60 %, i.e., allowing an output value $F > 0$. We need to note here that no_action has a default output value $F = 0$, thus a positive output value $F > 0$ is necessary for an action to be selected.

Notice that the relative load difference between agents that are about to form an *authority* relation (superior-subordinate) does not have an absolute value, as their relation expresses inequality, unlike a peer relation which expresses equality. Moreover, when agents are considering the *formation* of another relation, the "total" $l_{x,tot}$ and $l_{y,tot}$ loads are used in the calculation, while the pair's $l_{x,y}$ and $l_{y,x}$ loads are used when some agent x considers *dissolving* a relation with some y. Intuitively, this is because dissolving an existing relation is entirely up to the pair of agents that joined the relation in question. On the other hand, when two agents consider establishing a relation, the aggregated load from all other agents they are related to within the settlement has to be taken into account, since such a matter involves the "status" of both agents within the organization—which is associated with the overall to-date load of the agents.

Notice also that, in reality, both agents x and y would agree on their deliberation on F for any action: for instance, they would agree on the value of action $form\_auth_{x,y}$ (i.e., on the utility of x being superior to y), as they would agree on their evaluation for $form\_auth_{y,x}$. However, these values need not be calculated twice. Instead, to avoid redundancy, we ensure that y is the one calculating $form\_auth_{x,y}$ (and, similarly, $rmv\_auth_{x,y}$, $form\_peer_{x,y}$, and $rmv\_peer_{x,y}$), while x is the one evaluating $form\_auth_{y,x}$ (and, similarly, $rmv\_auth_{y,x}$, $form\_peer_{y,x}$, and $rmv\_peer_{y,x}$).

Now, given the central role of the limit ratio L used in the social re-organization decisions above, this model parameter can be actually better understood as being associated with a key social organization-related concept. Specifically, it can be easily linked to a "social barrier" that agents need to overcome in order to achieve social mobility: the value of any potential changes in social relations, is clearly linked to overcoming such a barrier (cf. Table 1). Thus, the value of L represents the "height" of such a "social barrier". To put it otherwise, L can be viewed as a metric of the *power distance* characterizing a given society. According to Andrighetto et al. [1], the *power distance* concept represents the extent to which the less powerful members of a society expect and accept that power and rights are distributed unequally, i.e., the extent to which stratification exists within a given social group.

The aforementioned re-organization process is continuous and employable by any agent on every time step. Moreover, it is key to sustaining the settlement and improving its viability, as also verified in our simulations.[11]

4.3 Self-organization algorithm modifications

Now, the *main* modifications[12] with respect to the self-organization algorithm in the work of Kota [44,45] 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 reorganization actions evaluation function F. Our self-organization method aims to facilitate a targeted redistribution of wealth. Given this, F employs the notion of a *relative* load difference among agents (unlike [44,45]). 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 A case study: simulating an Early Minoan Society

In this section, we describe the employment of the generic model presented above for the simulation of agents residing at the *Malia* area at the eastern part of the island of Crete during the Early Bronze Age. The exact modeling area is depicted in Fig. 5. It includes the Malia–Sissi–Mochos area, and also the Lassithi Plateau (near its centre and to the south).

[11] Note that dissolving "improper" existing relations, improves the efficiency of the agents' decision-making process, since there are fewer relations to consider when allocating tasks.

[12] There are other minor differences with the work of Kota et al. [44,45]. 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.

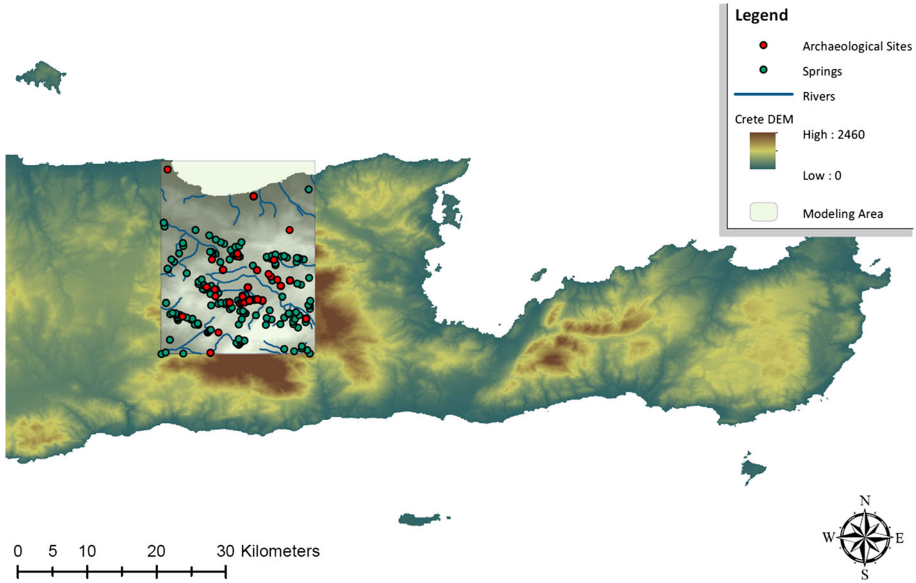


Fig. 5 Modeling area including settlements near Malia, Sissi and the Lassithi Plateau

Several ancient civilizations existed in the Aegean Sea during the Bronze Age, with the Crete island being associated with the Minoan civilization, which came to dominate the islands and the shorelines of the Aegean Sea. A significant shift in the early Minoans human existence and lifestyle was brought when crop farming was first developed. Previous reliance on a nomadic hunter–gatherer way of subsistence, was in time replaced by reliance on the produce of cultivated lands [30]. These developments are assumed to have had great impact on the growth of settlements, encouraging the concentration of local population. As a result, population density may have been relatively high, and agricultural activities more intense in the vicinity of settlements, while at the same time more remote regions were probably losing population, with land that was potentially quite productive going out of use [14].

From the sociological point of view, however, we do not have enough information about what kind of relationships existed between the Minoans or how this ancient civilization was organized before the "post-palatial" (Late Minoan) period.[13] Archaeological evidence strongly suggests that the Minoans were agriculturalists and pastoralists [32], as well as traders, and their cultural contacts reached far beyond the island of Crete—from Greece to Egypt to Anatolia [34].

Moreover, it is generally believed that there was little internal armed conflict in Minoan Crete itself, until the following Mycenaean period. Starting from these points of departure, there are several alternatives (originating in various traditional sociological approaches—social conflict, functionalism, interactionism, etc.) that may be suggested for the Minoans' social organization and subsistence [13]. Archaeologists still struggle to find if there are any

[13] The "Eteocretans", as they were called by Homer long time before the "Minoan" term that was coined by Arthur Evans after the mythic "King Minos", were farmers as well as traders in the whole Aegean [66], who had survived a natural catastrophe, possibly an earthquake and an eruption of the Thera volcano (such an eruption is often identified as a catastrophic natural event leading to the Minoans' rapid collapse [49]). Unlike what was the case in the Mellars model of the EOS project [20] (see Sect. 2), the wealth of environmental resources sustaining the Minoan civilization is not our focus of attention here.

signs of a "settlement hierarchy" in the "Prepalatial", Early Bronze Age period, based on the variation of settlement sizes within a region, or by the number of "tholos" graves in use in each cemetery (which serve as an indirect way of estimating settlement population) [57]. Renfrew and Cherry [53,55] argue that interactions between *different sociopolitical entities* are of a particular importance in the emergence of complexity within a society, while some archaeologists argue that a strongly stratified society can be assumed to have existed well before the end of the Neolithic period [8].

Although any such specific hypothesis can of course be the subject of modeling, our main concern here is to keep the model as generic as possible, in order to obtain clues about the underlying organization of the society and its evolution. In the simulations below, the simulated time interval (of 2000 years) spans essentially the entire Minoan Bronze Age (ca. 3100–1100 BCE). However, we are interested in interpretations about the *Early Minoan (EM)* period (ca. 3100/3000–2000 BCE) for which no clear evidence of social stratification exists [26]; and not the *Middle Minoan (MM)* (ca. 2000–1600 BCE) or the *Late Minoan (LM)* (ca. 1600–1100 BCE) periods, during which several localities on the island developed into centers of commerce and handwork, such as the Minoan Palaces.[14] Thus, we try to explore the social organization in the micro-level of such an early (EM) society, i.e. the organization evolution through interactions of individual "household" agents, about which little or no evidence can be obtained, rather than interactions between "settlement" agents in the macro-level (MM and LM period).[15]

The multiagent model can be implemented using a number of object-oriented languages, modeling toolkits, and platforms, each bearing certain advantages and disadvantages. While programming from the bottom up allows complete control over every aspect of the agent-based model, this can be a time-consuming option. Model implementation can be burdensome and considerable time can be spent on non-content specific aspects such as graphical user interfaces (GUI's), visualization and data importing. Toolkits do not require substantial coding experience and provide conceptual frameworks and templates that allow the user to design a customized model. Utilization of such software is particularly useful for rapid development of basic or prototype models. The main drawback is that researchers are restricted to the design framework supported by the software and may be unable to extend it or integrate additional tools.

Our ABM was developed using the *NetLogo* modeling environment [67]. NetLogo runs on the Java virtual machine, so it works on all current major computer platforms—while its programming language is a Logo dialect extended to support agents. NetLogo has been used to develop applications in various disciplines, such as biology, physics, and social sciences.

Regardless of the convenience and advantages offered by any specific modeling toolkit, ABMs applied in social sciences and in particular in archaeological research, cannot be easily validated via simulation results—especially in situations where little or no evidence is available (e.g., the social organization of Late Neolithic or Early Bronze Age societies). Simply put, it is impossible to compare the model input–output transformations to the corresponding ones of "a real system", since only assumptions and theories actually exist. One should always be very careful with parameter initialisation, so that these are based on archaeological

[14] Archaeologists' minimal definition of the Minoan "Palaces" describes them as regional centers or settlements that mobilized resources through secondary rural centers i.e. redistribution centers or perhaps exchange markets [5,28,52].

[15] It is important to note that the early Bronze Age society we model here, is one relying on farming within an environment that offered less than plentiful resources; and that, unlike modern "egalitarian" societies like these of Eskimos or Kalahari bushmen, the early Minoan society was one that in fact most probably transitioned from an originally segmentary society to one possessing a state-like organization.

research respectful to cultural and material evidence. Moreover, special attention should be taken so that parameter calibration does not bias the results towards confirming a pre-adopted theory or assumption.

Nevertheless, the validation of the structural assumptions of the model itself is an easier task (if not a straightforward one). For example, we have already seen (cf. Fig. 3) that employing extensive instead of intensive agriculture leads to lower amounts of resources in storage, regardless of the social organization paradigm used. Thus, one would expect the simulation results to confirm that employing an *extensive* agricultural technology will lead to lower crop yield for the agents, compared to that of the *intensive* agricultural regime.

We now proceed to describe the parameter choices made for our specific case study.

5.1 Model instantiation

Model parameters were initialized to values set so that they correspond to estimates found in archaeological studies relevant to the period of concern, as follows:

Number of agents The number of agents in a given settlement is initialised to a random number between 1 and 10. This choice originates to the fact that the estimated per hectare population in an agricultural settlement [35] during the modelled era was from 100 up to 300. Thus, the user-defined variable of maximum number of individuals per cell was set to 100; as a consequence, the *maximum* number of agents per settlement's cell is 10,[16] i.e., 100 divided by the maximum number of inhabitants per household (default: 10).

Settlement size A settlement initially occupies one cell. The number of cells that a settlement occupies is the smallest integer greater than or equal to its current population size divided by the maximum number of individuals (per cell). Thus, a settlement extends to a number of cells proportional to that of its agents. Note that the settlement area is not the same as the farming area corresponding to the settlement, which is as described in Sect. 3.4.

Resource amount stored and level of resources The agent can store some resource amount for a (user defined) number of *yrs* years. This *yrs* also corresponds to a settlement period at a specific location after which the agent might consider migrating to another location (if during this period U_x is constantly less than u_x^{thres}). In our experiments in this section we use $yrs = 5$. Now, if the sum of a year's production size and the amount of stored energy falls below a critical "*hunger*" level (of u_x^{thres} kg), the agent will try to replenish it by asking others for help. The figure of 250 kg was used as the minimum amount of resources required per individual per year (res_{min}), based on [35]. The initial level of the environmental resources is defined as the agricultural production R_i of a cell i (Eq. 1).

Agent locations Household and settlement locations are (pseudo) randomly initialized.

Number of settlements per scenario This parameter is user-defined. Its default value was set, somewhat arbitrarily, to 2.

Agents migration radius This is the distance agents can migrate to in one time step. It is also user-defined. In our experiments in this section we set it 25 km (i.e., the entire modeling area), roughly the distance covered when traveling on foot in a day [6]. Thus, the resettling cost rc for an agent was considered negligible—there is no requirement for extra time for rest, stops, overnight stays, *etc.*.

Agents agricultural strategy As mentioned in Sect. 3.4 above, *intensive agriculture* produces 1500 kg/ha, while *extensive* agriculture leads to a production of 1000 kg/ha [35].

[16] *NetLogo* can support thousands of agents, though RAM limitations are inherent in the underlying Java VM and/or operating system.

Social organization paradigms As mentioned, an agent makes decisions based on one of the following social organization paradigms: *independent*, *sharing*, *egalitarian*, *hierarchical*, and *self-organized*. For the later, the ratio limit L is user-defined (default: $L = 60\,\%$).

5.2 Simulations and results

Various scenarios were taken into account for the experimental setup, with different parameterisation for: five different behavioural 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) was also taken into account in certain simulations [22]. When this is the case, the initial production μ of a cell receives a penalty up to a percent of its value, with cells located outside a 1250 m 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. By calculating density, in a sense one spreads the input values out over a surface. The magnitude at each aquifer location (line or point) is distributed throughout the modeled area, and a density value is calculated for each cell in the environment.[17] Since there is no available past vegetation data, at the beginning of each scenario resources where spread randomly over the land, but with resource amounts at a particular cell depending on its slope (as discussed in Sect. 3.1).

Each scenario was simulated for *thirty (30) runs*, generating a total of 30×5 (behavioural modes) $\times 2$ (agricultural strategies) $\times 2$ (settling near an aquifer required or not) $= 600$ simulation runs. In addition, we experimented further with the "self-organization" social behaviour, testing overall four different values (10, 40, 60 and 90 %) of the ratio limit L for each agricultural strategy considered, and for 30 simulation runs each, under the assumption that residing next to an aquifer is a required behaviour. We run many more simulations for validation and sensitivity analysis purposes. Simulation results were averaged for each time-step. In terms of time, the process can be quite expensive, since a single run (composed of 2000 yearly time steps) takes approximately 90 min on a 2.6 GHz computer. However, by employing additional computational power, the simulation process can be sped up significantly (e.g., via allocating a dedicated single-core node of a *cluster computer* to a run, all 600 runs mentioned above can be completed in less than a day).

All data processing and analysis tasks were performed with the Model Exploration Module (MEME) of MASS.[18] Results visualization (charts or histograms) was done in MATLAB's (R2012a) environment. Moreover, the random number generators introduced in parts of the model are obviously "pseudo-random". Thus, via using the same random "seeds", one may introduce the same opportunities for agents in the model simulations (i.e., same "random" initial agent locations of the various runs for each different scenario). In this way, our simulations can be reproducible by any interested party.

We now proceed to discuss our findings with respect to agents social organization behaviour and the agricultural schemes examined and try to present the advantages and disadvantages of them for the various scenarios in account.

[17] http://resources.arcgis.com.

[18] http://www.aitia.ai/en/web/iaws/mass.

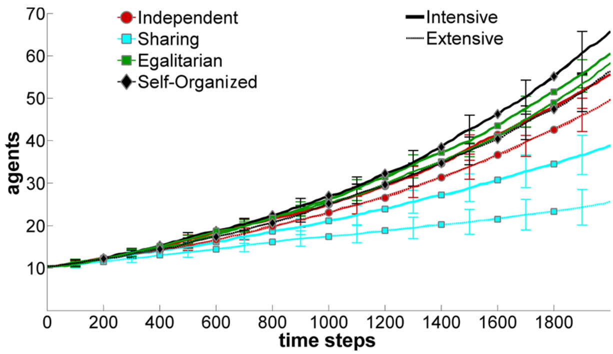


Fig. 6 Agent population (number of households) over 2000 yearly time-steps, *wrt.* intensive and extensive agricultural strategy, without a requirement for settling near an aquifer. *Error bars* indicate 95 % confidence intervals

5.2.1 Civilization sustainability

We begin with presenting our findings regarding the effect of the different social organization paradigms on the agent population. Simulation results are presented in Fig. 6 for both agricultural strategies. There was no requirement for settling near an aquifer for these simulations (i.e., there was no penalty for not settling near an aquifer location). Given the low population growth rates of the period, and the fact that the geomorphological characteristics of the area make resources scarce and energy production poor, it is clear that the population viability and growth observed in the simulations depends solely on the social organization paradigm in effect, and the agricultural regime used.

The simulation results of Fig. 6 indicate that population sizes in societies adopting the self-organization paradigm thrive under both agricultural strategies. Since self-organization results to a dynamic hierarchy governing the agents' relations, this result appears to support the case for archaeological theories assuming the existence of a "hierarchy-based" economy and a stratified social model; and the belief that stratification in Minoan Crete precedes the development of centers for higher-order regulation by several centuries [7,24].

Error bars corresponding to 95 % confidence intervals regarding agent population averages are also shown in that figure. In addition, we report that, for essentially any given simulation run corresponding to a specific *pseudo-random seed*, at each of which agents are operating in the same environment with the same opportunities, the ranking of the various social organization paradigms observed in Fig. 6 is maintained. That is, at almost every specific run, the *self-organization* social paradigm is better than the other social paradigms, egalitarian ranks second, and so on.[19]

Figure 7a shows that the number of settlements increases over time in proportion to agent population sizes; and that the number of agents per settlement seems to be higher when the *self-organization* social behaviour is adopted, as shown in Fig. 7b. Distribution of energy resources based on *self-organization* of agent relations, gives rise to dynamically emerging stratified social organization, and appears to be better in sustaining higher population sizes per settlement, especially when the *extensive* agricultural strategy (leading to less expected production) is employed. By contrast, when agents adopt the "egalitarian" social organization

[19] We do not show error bars for Figs. 7 and 8b, c (depicting settlements and agents per settlement). This is to avoid overloading these figures, and because of the apparent overlaps. We can report however that the *standard error* observed in those results is at most 1.

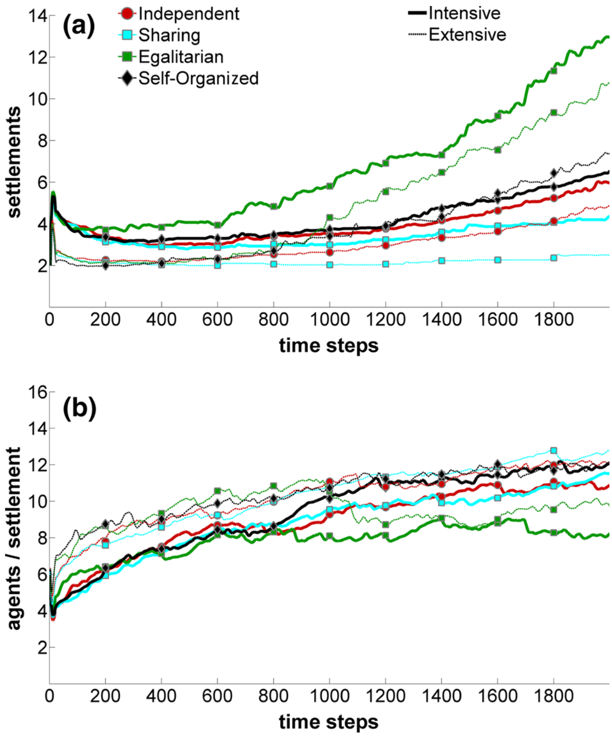


Fig. 7 Number of **a** settlements and **b** agents per settlement—over 2000 (yearly) time-steps *wrt.* intensive and extensive agricultural strategy, without a requirement for settling near an aquifer

paradigm, the emerging development of many "small-size" settlements seems to be the way for survival over time. This fact is in contrast to archaeological evidence for larger settlements (towns and "palaces") eventually coming to existence during the Middle/Late Minoan period (ca. 2000-1100 BCE) [61].[20] Thus, though the simulation results of Fig. 6 seem to not deny the possibility of viability for an egalitarian societal model, it is highly unlikely that such a model would have been able to sustain itself for 2000 years, given its observed "requirement" for being developed primarily within small settlements.

The *independent* and the *sharing* social behaviours also achieve numbers of agents per settlement that are equally high to those achieved by the self-organization one. The fact, however, is rendered meaningless, since they exhibit much lower numbers of agents and settlements, and they are not able to reach the estimated population growth rates for that period (see Sect. 3.3). Indeed, this is confirmed in our results of Table 2, considering an average initial population size of $N_0 = 50$ inhabitants over 30 simulation runs for any given scenario, and a steady growth rate of $r = 0.1\,\%$.[21]

[20] During the Early Minoan period (3000-2000 BCE), however, reviews of archaeological evidence for the Pre-palatial society visualize a "wholly undifferentiated" landscape, comprising "very small scale autonomous local units" of a "small-scale intensive farming model", with no convincing evidence for "wealthy elites" [26]. This society later gave its place to the "Palaces" of the Middle/Late Minoan periods.

[21] The steady population growth rate r is achieved assuming agents are consuming adequate resources (cf. Sect. 3.3). In that case, the expected population size N after t (yearly) time steps is given by the equation $N = N_0 * (1 + r)^t$ (where N_0 is the initial population).

Table 2 Individuals population size (and corresponding achieved percentage of estimated expected population size at the end of the modeled period) per social organization model, wrt. agricultural technology in use and the requirement for settling near an aquifer being false or true

Aquifer requirement	False		True	
Agricultural strategy:	Intensive	Extensive	Intensive	Extensive
Independent	238 (64 %)	208 (57 %)	183 (50 %)	139 (39 %)
Sharing	173 (48 %)	111 (32 %)	120 (34 %)	75 (23 %)
Egalitarian	262 (71 %)	252 (68 %)	220 (60 %)	176 (49 %)
Self-organized	278 (75 %)	243 (66 %)	233 (63 %)	172 (48 %)

As a final note, the overall agent population grows much larger when the *intensive* agricultural strategy is used rather than the *extensive* one; this is expected, since resources harvested each year by agents utilizing an *extensive* agricultural strategy are generally lower in quantity (cf. Fig. 3).

The Importance of aquifers

Now, landscapes near aquifers are particularly valuable to archaeology, because these environments were frequently the focus of human occupation and crucial to the rise of irrigation, agriculture and urban civilisation [54]. In fact, archaeologists consider it very unlikely that human settlements in the Minoan times were established far from aquifers [3,22]. To this end, agents in our model might need to consider the proximity of an aquifer, when settling to a new location. From this point onwards, all our simulation results will involve scenarios where agents are required to settle near an aquifer, unless stated otherwise.

The simulation results of Fig. 8 are entirely similar to the results obtained in Figs. 6 and 7, thereby corroborating the conclusions drawn above. There is, of course, one difference. As described earlier, when an agent is required to settle near an aquifer location, there is a penalty value introduced in the expected production for cells distant from aquifer locations. Thus, there are limited choices for cells to settle in. Therefore, it is expected that regardless of the social organization model adopted or agricultural strategy employed, agents and settlements numbers will drop in this scenario. Results in Fig. 8 confirm this intuition.

We also report our findings regarding the agent utility in this scenario (Fig. 9a). Although it is slightly decreasing over time,[22] it is sustained in approximately stable and equal levels for both the self-organized and egalitarian social behaviours, while it is considerably lower for the "independent" and "sharing" one—hence explaining the lower agent population and settlement organization sizes in Fig. 8.

Moreover, the *produce stored* by the agents in order to distribute and/or use when necessity arises, seems to be considerably higher for the self-organized rather than the egalitarian social organization paradigm for both agricultural strategies employed by the agents, as presented in Fig. 9b. Higher storage values that are seen when agents employ an "independent" social organization are due to their essentially "selfish", non-distributive behaviour. Even when the "sharing" social organization paradigm is in use, with a cooperative spirit present among agent relations, higher storage values observed are due to unexploited resources stored by "wealthier" agents exploiting their limited household sizes.

[22] This is not unexpected, since, as the individuals' population increases, soil erosion leads to a slow production decrease (cf. Eq. 1), and thus to a decay in utility.

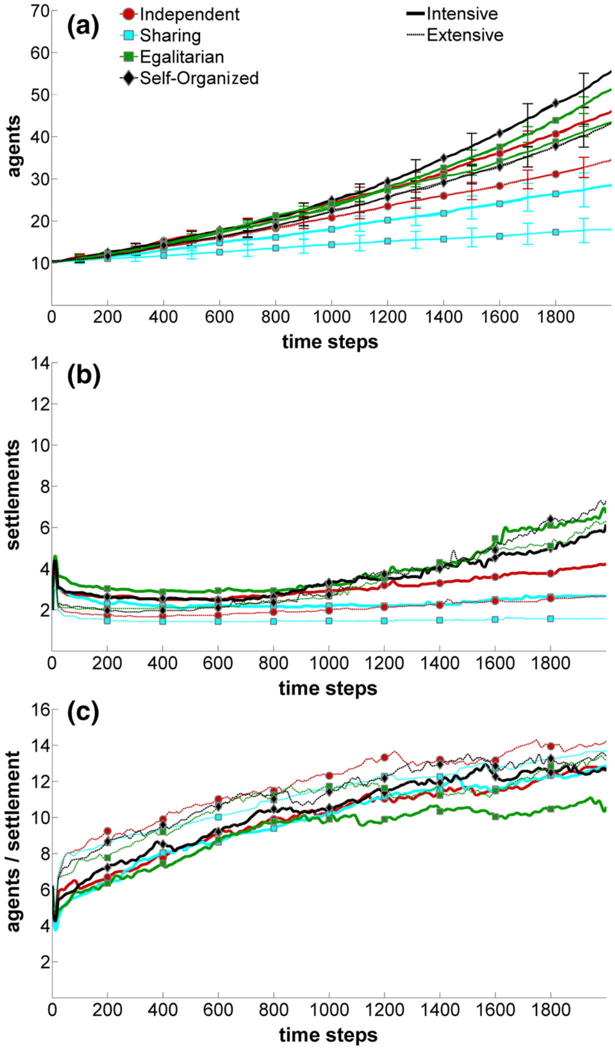


Fig. 8 Number of **a** agents, **b** settlements, and **c** agents per settlement—over 2000 (yearly) time-steps *wrt.* intensive and extensive agricultural strategy with a requirement for settling near an aquifer. *Error bars* indicate 95 % confidence intervals

We close this section by noting that, regardless of aquifer proximity or agricultural strategy employed, settlements are concentrated near actual (depicted) archaeological sites at the coastal Malia regions, or at the Lassithi plateau (black coloured region in the middle of the modeling area) presented in Fig. 10. This is a phenomenon imposed by the modeling area's geomorphological characteristics (see Eq. 1).[23]

[23] For interest, we note that this is also in agreement to genetic evidence regarding the continuity of the existence of a Minoan population at the Lassithi plateau [38].

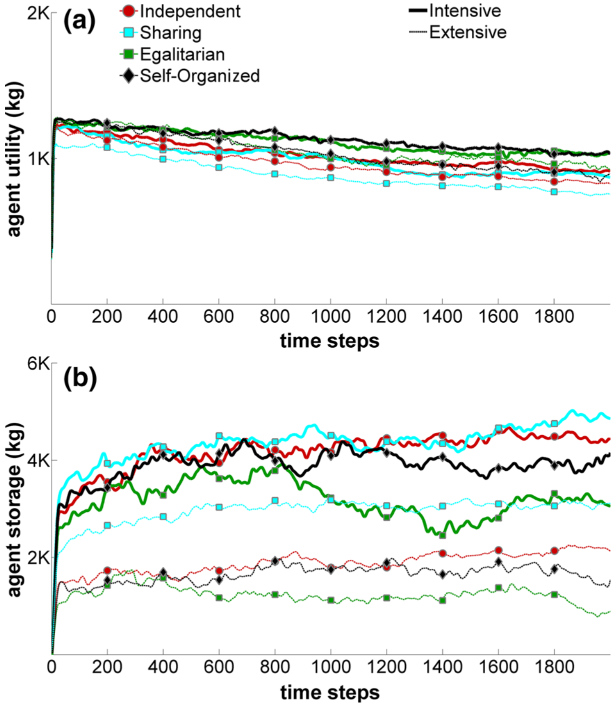


Fig. 9 **a** Utility and **b** storage values of (household) agents over 2000 (yearly) time-steps *wrt.* intensive and extensive agricultural strategy with a requirement for settling near an aquifer

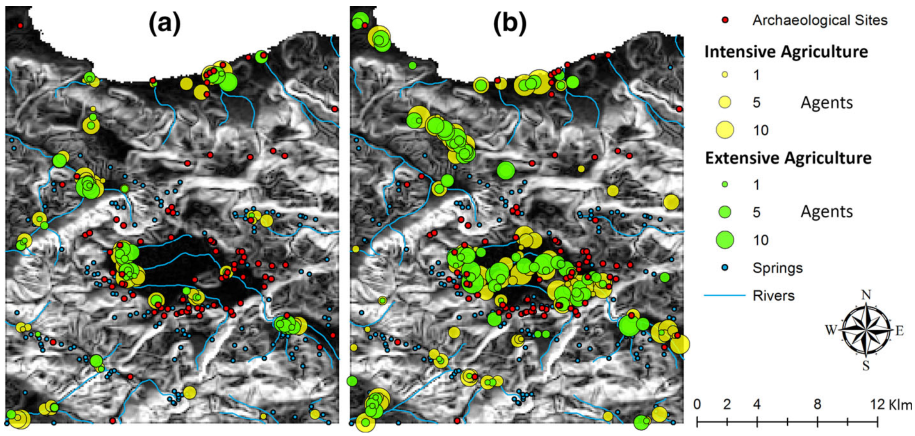


Fig. 10 Settlement locations proportional to agent population size after 2000 years; **a** with and **b** without a requirement for settling near an aquifer, employing a *self-organization* behaviour

5.2.2 Self-organization: validation and insights

We now focus more on the self-organization social organization paradigm. The *egalitarian* and *sharing* social behaviours, do not actually add any real complexity in the system's working process, since agents are essentially offered the same opportunities to survive. The

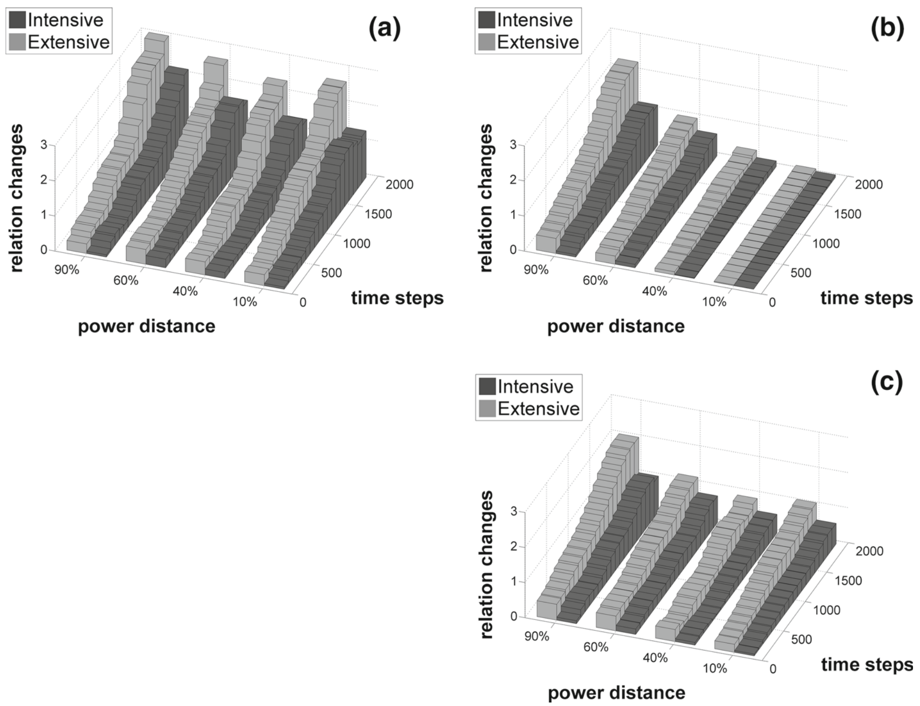


Fig. 11 Average number of agent relation changes to **a** authority, **b** peer, and **c** acquaintance relation per century for various power distance rates *wrt.* intensive and extensive agricultural strategy

re-organization of the agents' relations on the other hand, based on their the past and current experience on relative difference of exchanged energy and, hence, their "social status", generates a complexity that needs to be appropriately validated.

As such, it is only appropriate that the behaviour of the self-organization paradigm needs to be studied and validated with respect to the "power distance" concept, which is central to the essence of stratified societies. In our model, the parameter that is best associated with the power distance concept is the *limit ratio* L employed in the re-organization actions' evaluation process (cf. Sect. 4.2 above). Therefore, the main question we ask in this section is the following. What is the agent organization's response to different degrees of power distance imposed upon the society?

As the power distance grows between superior and subordinate agents in an *authority* relation, we expect more peer relations to be formed among agents in the organization, expanding the (social) organization's stratified structure both horizontally and vertically. This is due to utility maximization considerations in the individual and organizational level, and due to the produce redistribution process. Simulation results show exactly this phenomenon, as we increase the society's power distance (the L action evaluation parameter).

Specifically, relation changes to a *peer* relation within an organization increase proportionally to the power distance rate considered, as shown in Fig. 11b. When agents (in need) distribute produce with respect to to their (type) relations, higher power distance rates (e.g., 90 %) seem to promote the development of additional peer relations among agents, expanding the emerging hierarchy "horizontally", rather than "vertically" (as observed for lower power distance rates), a phenomenon that is intuitively correct. The number of relation changes to an

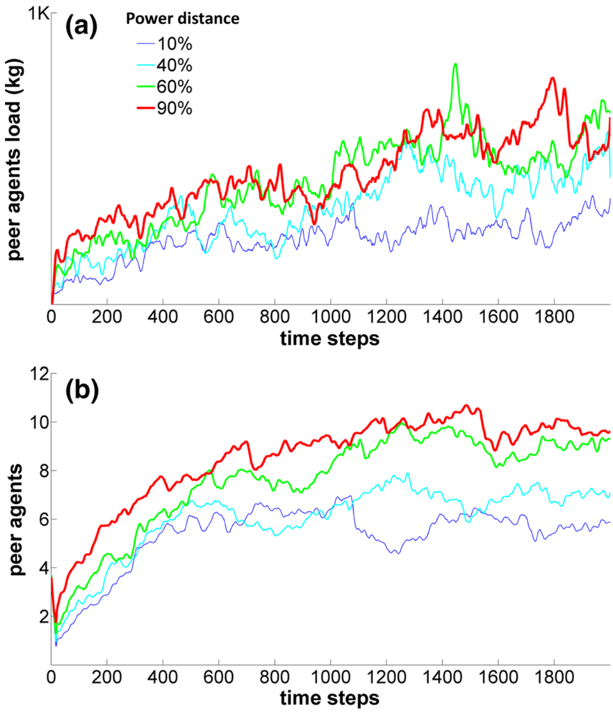


Fig. 12 **a** Load and **b** number of peer agents for various power distance rates over 2000 (yearly) time-steps *wrt.* extensive agricultural strategy

authority relation (Fig. 11a) are at about equal level, regardless of variation in power distance. On the other hand, relation changes to an acquaintance relation (Fig. 11c) are observed for higher power distance rates, especially when the *extensive* agricultural strategy is employed by the agents, where less resource production occurs. Moreover, the number of *peer* agents, as well as their corresponding overall *load* of exchanges (which is linked to social status), increase proportionally to the power distance, as presented in Fig. 12.

Now, although the agents may "expand" their cultivation areas under the *extensive* agricultural strategy, they actually "gain" less energy amount harvested and stored (see Fig. 3). Thus, the agents are "forced" to reorganize and change their relations among them even more frequently than under the intensive agricultural regime, in order to stabilise their produce exchange network, and promote viability both in the individual and the organizational level. This is evident in Fig. 11.

Overall, the range of power distance in a society, appears to have an impact on the number of agents' relation changes, the type of relations the agents create, and the volume of resources agents hand over to others. We note, however, that there is a remarkably low average number of relation changes over time, specifically, less than 3, as seen in Fig. 11.)

By contrast, the range of power distance within a stratified society seems to have a minor impact on the overall welfare of the agents. As seen in Fig. 13a, agent utility remains almost invariable to lower or higher power distance among agent relations. Similarly, the produce stored by the agents (Fig. 13a), as well as the agents population size, shown in Fig. 13b, do not appear to be influenced by the underlying societal power distance.

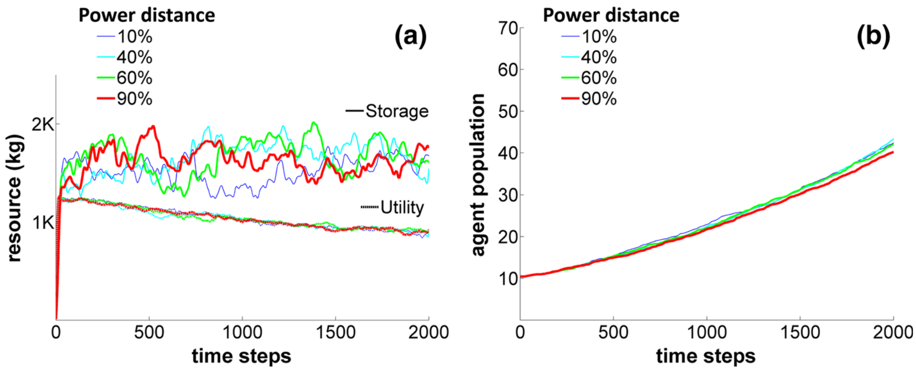


Fig. 13 Agents **a** utility, storage and **b** population size for various power distance rates over 2000 (yearly) time-steps *wrt.* extensive agricultural strategy

5.2.3 Further observations

Certainly, from the social sciences perspective, and in particular that of archaeology, there can be several (subjective) explanations or interpretations arising from any given simulation result. For example, our simulation results on population growth for the period under examination, show that both the "egalitarian" and self-organized social models are able to follow the underlying growth rate values. However, while the number of organization settlements grows with an approximately equal rate for both the egalitarian and self-organized social organization paradigms, the number of "household" agents per settlement does not. This is in line with social, and especially, archaeological theories presuming that complex communities have larger population sizes than their egalitarian predecessors [54].

In addition, considering that the Minoan Palaces and larger towns are unlikely to have arisen under an "egalitarian" social organization of "small-size" settlements (see Figs. 7, 8c), one could infer that a distributive social organization model which gave rise to a dynamic social hierarchy, such as the self-organization one studied here, is more probable to have existed for the 2000 year period under study. Furthermore, the resource energy *stored* by the agents in order to distribute and/or use when necessity comes, seems to be considerably higher for the self-organized rather than for the egalitarian social organization paradigm in both agricultural strategies employed by the agents.

From a socio-political point of view, it is interesting that a class of agents that are exclusively "peers" *does not* actually exist among the agents, while an "authority" relation does uniformly exist, representing a "genuine" agent type. (The term "genuine" or "non-composite" agent type signifies that the agent is joined with other agents in the settlement with the corresponding relation type only. For example, a "genuinely superior" agent is one that has subordinate agents only, a "genuinely subordinate" agent is the one that has only superior agents, and a "genuine peer" agent is the one that has only peer relations with other agents.) That is, the society is divided among *superiors* and *subordinates*. This is obvious in Fig. 14, where "genuine" peer agent types do not exist. Rather, forming a peer relation seems to be the intermediate step in a social status redistribution process within the settlement.

Thus, with self-organization determining the social relations network, *a "heterarchical" social structure actually emerges*, rather than a clear hierarchical structure evident in later periods. A "heterarchy" is a system of organization where its elements are "unranked" (non-hierarchical) or where they possess the potential to be ranked by a number of different ways [15], e.g., in our case, by the exchanged *load* among agents throughout the organization's

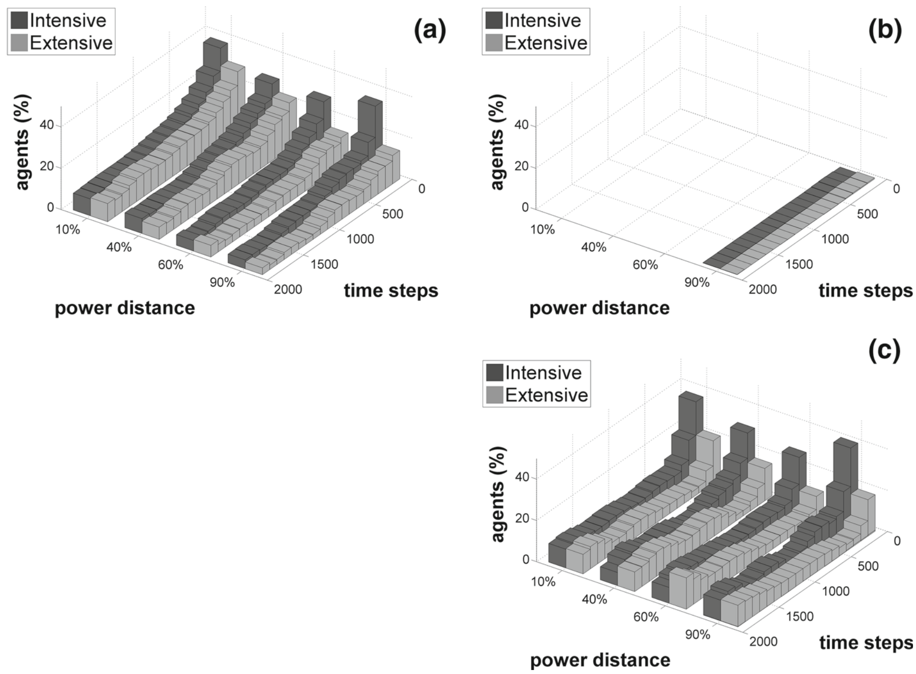


Fig. 14 Percentage of agents with non-composite **a** superior, **b** peer, and **c** subordinate relation per centennial time step, for various power distance rates *wrt.* both agricultural strategies

lifetime. Socially, a heterarchy distributes privilege and decision-making among the agents, while a hierarchy assigns more power and privilege to the members higher in the structure. In a heterarchical system, domination and subordinate relations can be reversed, and privileges or status can be "redistributed" in each time-step, following the needs of the organization.

Self-organization versus static hierarchical structures

As archaeologists assume a hierarchical social structure in later periods of the Cretan civilisation [9,24], we now focus on a direct comparison of a social organization with "static" hierarchical relations among agents, with the "heterarchical" social structure dynamically emerging through the underlying self-organization behaviour.

Agent and settlement population sizes are presented in Fig. 15. Although the growth rate and final population numbers are in general similar, we observe a great advantage for the self-organization behaviour with respect to population growth, when settling near an aquifer is not a required behaviour, and the intensive agricultural strategy is used (Fig. 15a). Settlement numbers are at about the same levels for both social organization paradigms (Fig. 15b).

Then, in Fig. 15c we observe that the self-organization social paradigm appears to have a slight advantage against the static hierarchical one, with respect to settlement population sizes—regardless of agricultural strategy employed, or of whether settling near aquifers is a required behaviour. Self-organized agent societies appear, on average, to be giving rise to larger settlements during their evolution. Note that both the static hierarchical and the self-organization paradigms, maintain larger settlement population sizes than the "egalitarian" distributive one (cf. Figs. 7b, 8c). However, agents utility as well as the produce stored by the agents, is at approximately the same levels per scenario for both the self-organization and the static hierarchical social organization paradigm as seen in Fig. 16.

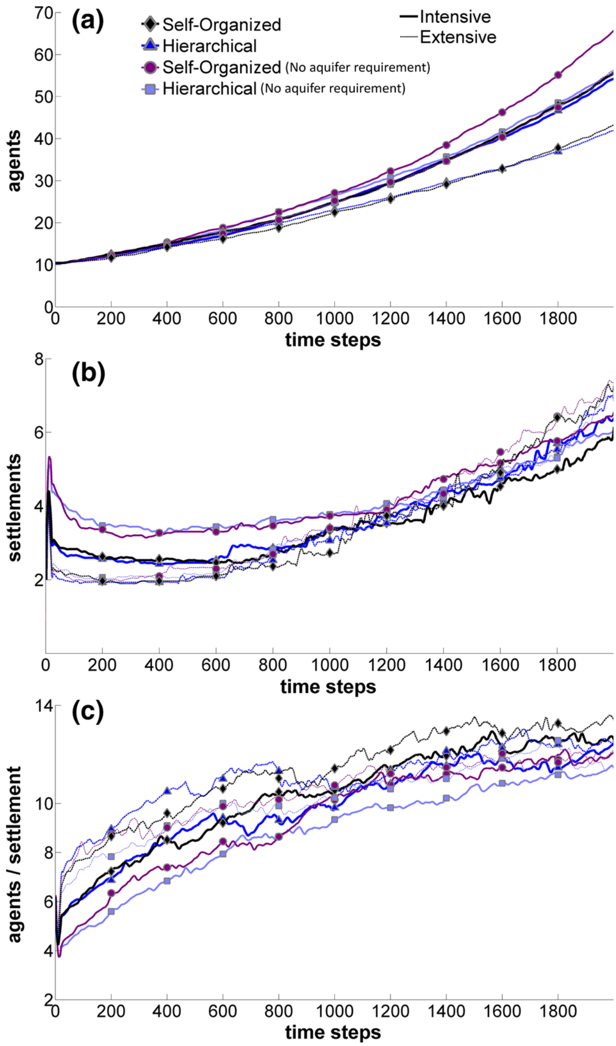


Fig. 15 Number of household **a** agents, **b** settlements and **c** agents per settlement over 2000 (yearly) time-steps *wrt.* intensive and extensive agricultural strategy, and with settling near an aquifer being a requirement or not

Overall, it seems that a static hierarchical structure exhibits a similar viability potential with that of the 'heterarchical" social structure emerging through self-organization behaviour.

However, the later appears to have an advantage in certain scenarios. Moreover, from an archaeological and historical point of view, it is rather improbable that a static hierarchical structure would have existed in Crete for the entire Bronze Age (the 2000 years period in question), especially for the modeled Malia area [58].

Agent Migrations

Besides agent population, storage, utility and organization sizes, we also examined the patterns of agent migrations related to the social organization paradigms under study. Overall, the average number of agent migrations per (yearly) time-step is less than 0.05; specifically,

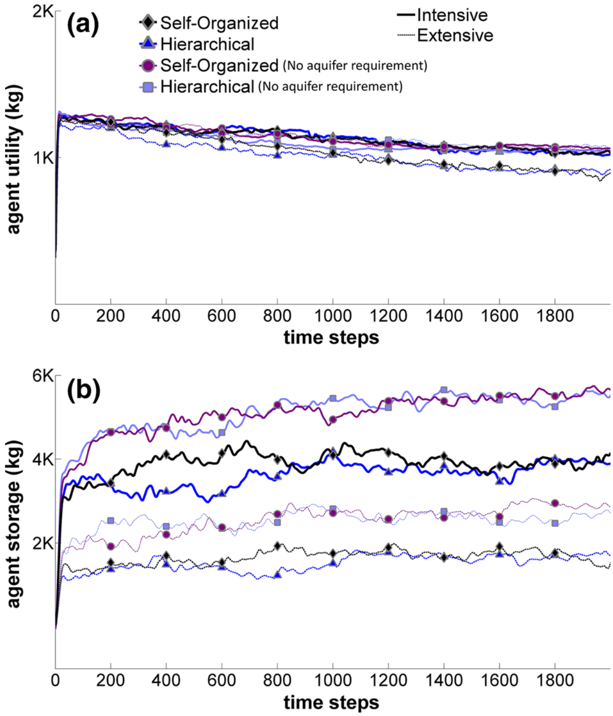


Fig. 16 Agents **a** utility and **b** storage over 2000 (yearly) time-steps *wrt.* intensive and extensive agricultural strategy, and with settling near an aquifer being a requirement or not

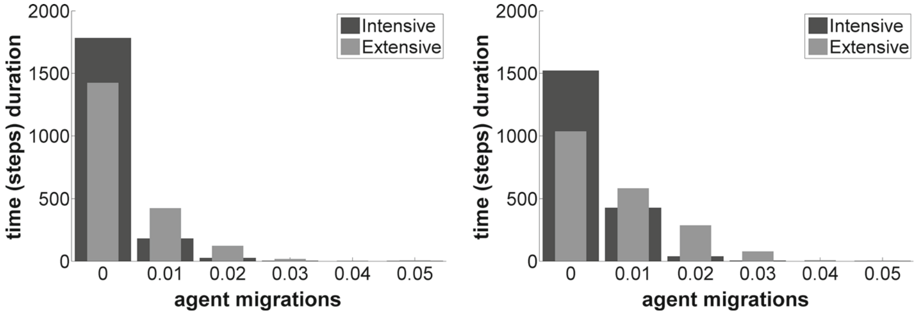


Fig. 17 Histogram of number of agent migrations per time step for (*left*) egalitarian and (*right*) self-organized social organization paradigms *wrt.* both agricultural strategies

it is less than 0.01 for most of the simulation's time duration, with higher values recorded at the end of the simulations where more agents are observed (Fig. 17).

Although the number of agent migrations seems to be increasing over time along with population sizes, mainly for the self-organized behaviour and especially when an *extensive* agricultural strategy is applied, agents migration activity can be considered trivial, since an agent considers migrating only once in a millennium. Thus, the migration ability modeled, appears to truly serve as the ultimate workaround for agents, when no other sustainability option is provided by their (social) organization (i.e., not enough resources are provided/distributed, or "overcrowding" is observed when organization is at maximum *carrying capacity*). It is definitely not a major agent activity. Thus, the population indeed corresponds better to "settled agriculturalists", rather than to agents with temporary settlements only.

5.2.4 Non-myopic agent decision-making

In this section, we illustrate the fact that our model can readily support non-myopic agent action selection. Specifically, we define a simple example for a (sophisticated) household agent decision-making process, which uses an MDP [50] to decide on migration (or settlement) policies, and compare the viability (in terms of population growth over 2000 years) of the resulting agent societies against that of myopic ones.

At each time step of the agent decision-making problem, an agent once again needs to decide on (*a*) whether it should stay, wait and thus, *settle* to its current location for at least yrs years in a row, while cultivating the surrounding area, or (*b*) *migrate* to another, more promising settlement location (and settling there for yrs years). However, the agent decisions now take the long-term effects of agent actions into account, and arise as the results of solving finite-horizon MDPs that determine their long-term value—assuming a specific planning horizon of h decision time steps, or "stages". Agent actions result to transitions to specific locations, corresponding to MDP states (and which are potentially different than the current one). As before, agents can only migrate to states that correspond to *unused* cells. The long-term value of being at state s where one can choose to take some action a (i.e., to settle at s or migrate to one of a number of candidate locations), can then be determined via the solution of a system of Bellman optimality equations:

$$V(s)=\max_a\{\sum_{s'} P_a(s,s')(R_a(s,s')+V(s'))\} \tag{7}$$

where transitions from s to s' range over the planning horizon h, $R_a(s,s')$ is the *immediate reward* resulting from transition to state s' (i.e., the value of cultivating the lands for yrs years at s', given the expected agricultural production of the corresponding "field" cells associated with s', as described in Sect. 3.2), and $P_a(s,s')$ is the transition probability to s' when taking action a at s. This $V(s)$ state value essentially replaces its myopic estimate of Eq. 3. Thus, the utility of an agent x at a given location s is now:

$$U_x = V(s) \tag{8}$$

In our implementation, the MDP solution determining the optimal $V(s)$ values and migration policies is provided by the well-known *value iteration* algorithm [50]. However, in reality the dynamics of the setting within which an agent takes decisions are not stationary in our case. This is because the rewards related to a given environmental cell are not static, but fluctuate over time, as a result of population growth and of the various agents settlement and cultivation actions. Due to this fact, solving an MDP once cannot possibly provide a decisive answer to the agent decision problem. In order to combat this, the agent should at least be formulating and solving an MDP at every single time step.[24] To keep things as tractable as possible, however, we assume that the decision problem is only occurring (and, subsequently, an MDP needs to be solved) if the agent $storage = 0$, and its utility from cultivating the lands at the current location has been dangerously low, i.e., $U_x < u_x^{thres}$, for at least yrs in

[24] We do not claim that this is the most appropriate way to tackle non-stationarity. Solving non-stationary, multi-agent MDPs is not one of our goals in this paper.

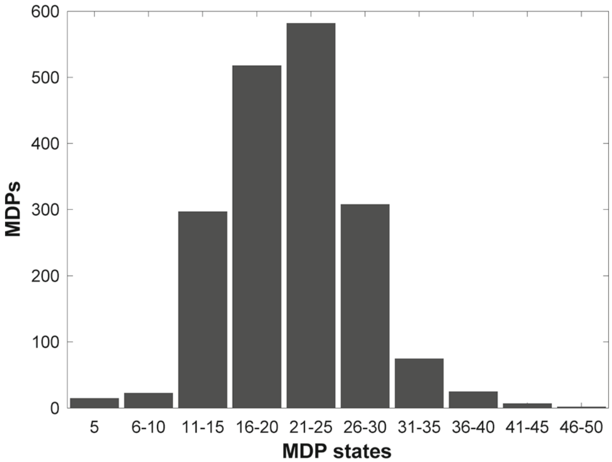


Fig. 18 Numbers of dynamically created MDPs in an average simulation run, along with corresponding numbers of their states. Averaging was over 30 simulation runs

a row (in our experiments in this subsection, we set $yrs = 10$). Once an MDP solution has been provided for an agent, it then follows the resulting policy for h decision steps (each occurring every yrs simulation years); then, if the conditions above call for a re-evaluation of a settlement policy, yet another MDP is formulated and solved. Figure 18 shows the numbers of dynamically created MDPs in an average simulation run.

We have made several additional assumptions in order to ensure tractability while keeping the decision problem as realistic as possible—given also that it is unlikely that Bronze Age agents would have been able for very long-term planning, while they most probably would be facing considerable movement difficulties. An agent's migration options are assumed to be restricted by both migration distance and terrain elevation. Thus, the states reachable from a specific state s correspond to locations within a given migration radius $r_{max} = 5$ km. Even with this restriction, an agent is still able to cover almost the entire environmental area within 3 migration "hops" (Fig. 19). Thus, in our experiments we assume a finite planning horizon of 3 stages; and set the h parameter's value to 3 also.

Moreover, we classify the states according to environmental elevation as *low*, *medium*, and *high elevation*, and assume that agent movement is restricted given its current elevation state, as shown in Fig. 20. For instance, if the current (state) agent location is at a *low* elevation level, it can only transit to a *low elevation* or to a *medium elevation* state (within its migration radius) only, and not to *high elevation* ones.

These restrictions reflect difficulty of movement and transport between less or more mountainous areas. Finally, we assume that the agent is allowed to transit to m states per elevation level at each time step; and state transitions are deterministic. In our experiments reported below, m was set to value of 1 for computational efficiency purposes.

Despite these restrictions, it takes up to 3 min to formulate an MDP and solve the decision problem of just a single agent at one time step, on a 2.6 GHz computer. However, *solving* the MDP via value iteration is *not* the main computational bottleneck: executing the value iteration algorithm takes only a few seconds—i.e. just a tiny fraction of the aforementioned time. Rather, the delays are linked to *building* the MDP, i.e., mainly determining the cells' immediate rewards, due to speed limitations of the Netlogo software.[25] Further problems arise

[25] See, e.g., https://github.com/NetLogo/NetLogo/issues/402.

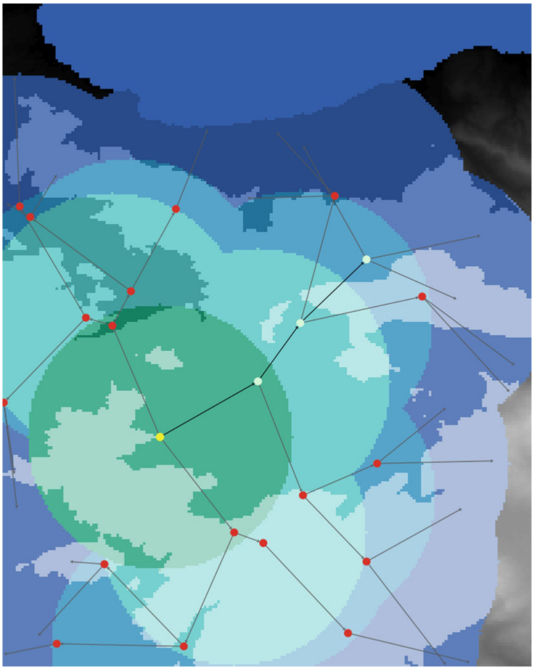


Fig. 19 An example of states (*red dots*) and transition actions (*grey lines*) for an agent's MDP. States of the optimal policy are shown (*white dots*) (Color figure online)

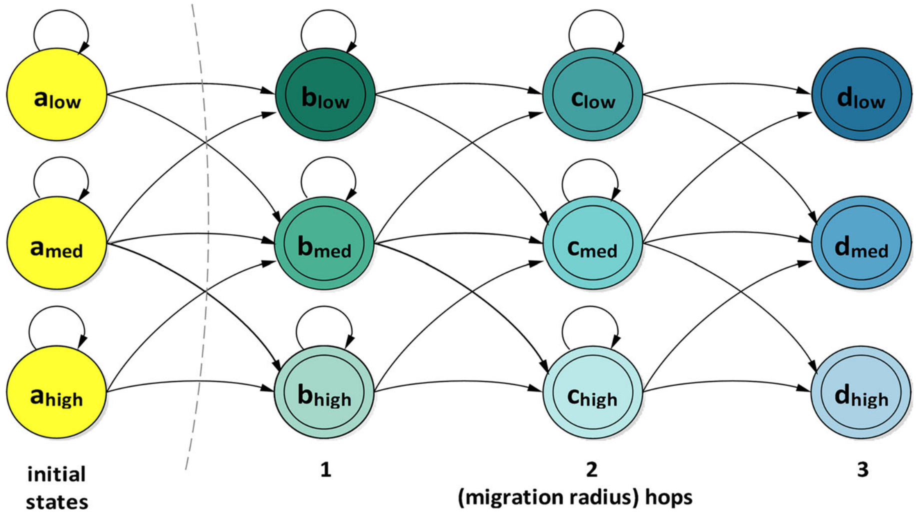


Fig. 20 States (*circles*), collections of states (*multiple circles*) and transition actions (*arrows*) for an agent's MDP considering a 3-stage planning horizon

from the fact that (*a*) multiple MDPs (corresponding to various agents planning problems) have to be dynamically built at any time step, due to the setting's non-stationarity; and (*b*) our ABM employs a fine resolution actual digital elevation model of the 50K cells modeling area.

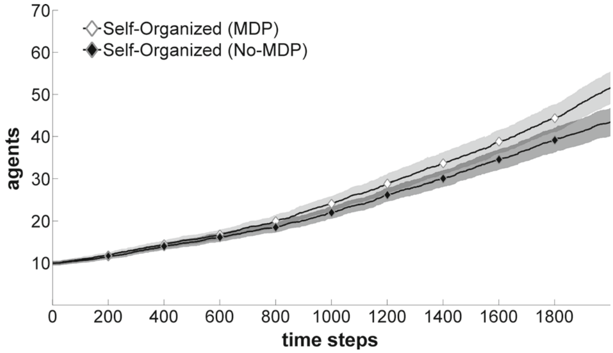


Fig. 21 Agents population (number of households) over 2000 yearly time steps, *wrt.* intensive agricultural strategy, with a requirement for settling near an aquifer, using an MDP for decision-making or not. *Error shading areas* indicate 95 % confidence intervals. Results are averages over 30 simulation runs

As a result, an entire 2000 years simulation run takes on average 7 h on a 2.6 GHz computer, when using the aforementioned parameter values.[26]

Even with these restrictions in place, our experimental results confirm the intuition that an ability to “plan-ahead” is beneficial to the agents. Specifically, Fig. 21 shows that, when compared to “myopic” agent societies, societies of agents that use MDPs for planning migration policies achieve population numbers that are on average higher across the entire 2000 years period.[27]

6 Conclusions and future work

Agent-based modeling has been used in archaeology for about 15 years now, because it has the ability to reflect properties of the real world, along with their evolution. In this work, we attempted to showcase how to incorporate MAS-originating concepts and algorithms in archaeology-specific ABMs. To that end, we designed and implemented a generic ABM system for archaeology research, adopting (as is common in the MAS literature) a utility-based agent architecture. Moreover, we incorporated into our ABM an appropriately modified *self-organization* method, originally proposed for modern-day agent organizations. Self-organization mechanisms have been observed in nature and biology and subsequently successfully applied in MAS research. However, such mechanisms had not been incorporated and tested in an archaeology simulations system before this paper.

We employed our system in order 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. Our simulation results show that agent societies that adopt self-organization exhibit an increased viability over the entire 2000 years of this period. Now, self-organization gives rise, naturally, to implicit agent hierarchies. As explained in Sect. 4, however, in our

[26] Of course, several efforts could have been undertaken to speed-up the process of dynamically defining and solving the MDPs—e.g., via re-using MDPs already solved for agents operating in nearby regions and nearby time-steps. However, this is not the focus of our work here: our experiments in this section simply intended to demonstrate that our model can readily incorporate non-myopic agent deliberations.

[27] We have ran additional experiments which confirm that increasing the value of m can be beneficial when state transitions are non-deterministic. Moreover, we can observe improvement when agents plan ahead more often (e.g., every 5 yrs instead of 10). We do not report further on these findings in this paper.

mechanism the wealthy are assumed to be helping out agents in need. Thus, our results in this paper should by no means be interpreted as providing evidence for the sustainability of exploitative hierarchical societies. Instead, they could rather be interpreted as an indication that *targeted wealth redistribution* works better than a blind one.

Moreover, the simulation results indicate that a *heterarchical* social structure, having emerged by the continuous re-adaptation of social relations among Minoan households, might well have existed in the area of study. This is in agreement with existing archaeological theories and data. Specifically, our results could provide support for the so-called "managerial" archaeological theories, which assume the existence of different social strata in Neolithic and Early Bronze Age Crete; and which consider this early stratification a pre-requisite for the emergence of the Minoan Palaces, and the hierarchical social structure evident in later periods [7,9,24].

In terms of future work, we need to run more scenarios with a variety of initialization setups (more[28] or fewer agents with different ranges of migration capabilities; different cell output values per agricultural technology, to model the use of advanced equipment or variable manpower; different aquifer proximity radius and penalty values; etc.). In addition, we 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. We are also interested in examining the economic and political interactions among settlements (as opposed to those among households alone), since such interactions were prevalent in later periods—perhaps via the employment of evolutionary game-theoretic methods. To this end, the topology of the underlying exchanges and commerce network will most probably have to be taken into account, to the extent this is provided by relevant historical records [23].

Finally, we plan to pursue the study of archaeological theories as the means to come up with intuitions, ideas, and algorithms for modeling agent societies and the emergence of agent collaboration; and to focus on devising novel algorithms for adaptation and self-organization methods, with potential application on archaeology-related ABMs.

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[28] We have run simulations involving an initial population of 100 agents, and the results we obtained were similar to those reported in this paper. Thus, we do not anticipate that a higher initial population of agents will substantially change the conclusions drawn from our work here.

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