Agent-Based Modeling of Past Societies and their Social Organization

by

Angelos Chliaoutakis

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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 thesis, we attempt to answer such questions using ideas mainly from multi-agent systems, game-theory, and agent-based modeling (ABM).

Specifically, we provide a generic ABM system, *AncientS-ABM*, for simulating and evaluating the potential social organization of an artificial ancient society, configured by available archaeological data. Unlike most existing agent-based models used in archaeology, our ABM framework includes completely autonomous, *utility-based* agents. It also incorporates different social organization paradigms, different decision-making processes, and also different cultivation technologies used in ancient societies. Equipped with such paradigms, the model allows us to explore the transition from a simple to a more complex society by focusing on the historical social dynamics; and to assess the influence of social organization on agents' population growth, agent community numbers, sizes and distribution.

Our ABM also blends, for the first time, ideas from *evolutionary game theory* with multi-agent systems' self-organization. We model the evolution of social behaviours in a population of strategically interacting agents in repeated games where they exchange resources (utility) with others. The results of the games contribute to both the continuous re-organization of the social structure, and the progressive adoption of the most successful agent strategies. Agent population is not fixed, but fluctuates over time, while agents in stage games also receive non-static payoffs, in contrast to most games studied in the literature. To tackle this, we present a novel formulation of the evolutionary dynamics via assessing agents' rather than strategies' fitness.

In addition, AncientS-ABM is able to also simulate societies *inter-community* interactions, by modeling the exchange and distribution across agent communities. In particular, we incorporate a trading sub-model by employing different *spatial interaction models* for simulating trade across agent settlements, in order to explore the resulting trading network's efficiency and its evolution at different points in time. We further utilize ideas from *graph theory* to analyze the trading network's structure, seeking to provide insights on the artificial society's organization on a higher level. Finally, we also extend our ABM by incorporating a *natural disaster* sub-model.

As a case study, we employ our ABM to evaluate the impact of the implemented social organization paradigms on an artificial Early Bronze Age "Minoan" society, located at different geographical parts of the island of Crete, Greece. 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 better sustainability for settlements consisting of and adopting a socio-economic organization model based on self-organization, where a "heterarchical" social structure emerges. Results also demonstrate that successful agent societies adopt an evolutionary approach where cooperation is an emergent strategic behaviour. In simulation scenarios where the natural disaster module was enabled, we observe noticeable changes in the settlements' distribution, relating to significantly higher migration rates immediately after the modeled Theran eruption. In addition, the initially cooperative behaviour is transformed to a non-cooperative one, thus providing support for archaeological theories suggesting that the volcanic eruption led to a clear breakdown of the Minoan socio-economic system. Moreover, we observe that modeling a trading network that favours settlements' importance rather than distance between settlement locations, can produce settlement patterns similar to the one that exist in archaeological record. The existence of some important resource-distribution centers, with possibly a strong hierarchy during the Early and Middle Minoan period, as well as significant resource-aggregation centers during the Late Minoan period, also arise as plausible possibilities via our agent-based model.

Περίληψη

Μερικά από τα πιο ενδιαφέροντα ερωτήματα σχετικά με τις πρώτες ανθρώπινες κοινωνίες, αφορούν την φύση και τον τρόπο οργάνωσής τους, καθώς και τις σχέσεις μεταξύ των μελών τους. Σε αυτή τη διατριβή, προσπαθήσαμε να απαντήσουμε σε τέτοια ερωτήματα χρησιμοποιώντας ιδέες προερχόμενες κυρίως από τρεις επιστημονικούς κλάδους: τα πολυπρακτορικά συστήματα, την θεωρία παιγνίων, και την μοντελοποίηση και προσομοίωση βασισμένη σε πράκτορες (Agent-Based Modeling, ABM).

Συγκεκριμένα, αναπτύξαμε ένα σύστημα (πολυ)πρακτορο-κεντρικής μοντελοποίησης, το AncientS-ABM, για την προσομοίωση και την αξιολόγηση της δυνητικής κοινωνικής οργάνωσης μιας (τεχνητής) αρχαίας κοινωνίας, το οποίο μπορεί να παραμετροποιηθεί από διαθέσιμα αρχαιολογικά δεδομένα. Σε αντίθεση με τα περισσότερα υπάρχοντα μοντέλα βασισμένα σε πράκτορες που χρησιμοποιούνται στην αρχαιολογία, το πρακτορο-κεντρικό σύστημά μας περιλαμβάνει πλήρως αυτόνομους πράκτορες, που είναι βασισμένοι στην αρχιτεκτονική πρακτόρων με βάση τη *χρησιμότητα*. Επίσης ενσωματώνει διαφορετικά παραδείγματα κοινωνικής οργάνωσης, διαφορετικές διαδικασίες λήψης αποφάσεων, καθώς και διαφορετικές γεωργικές τεχνολογίες (πρακτικές) που πιθανότατα χρησιμοποιούνταν στις αρχαίες κοινωνίες. Εφοδιασμένο με τέτοια παραδείγματα, το μοντέλο μας επιτρέπει να διερευνήσουμε τη μετάβαση από μια απλή σε μια πιο περίπλοκη κοινωνία εστιάζοντας στην ιστορική κοινωνική δυναμική· στοχεύοντας στην εκτίμηση της επίδρασης της κοινωνικής οργάνωσης στην ανάπτυξη του πληθυσμού των πρακτόρων, του αριθμού των κοινοτήτων-οικισμών, αλλά και του μεγέθους και της κατανομής αυτών των κοινοτήτων.

Επίσης, το μοντέλο μας συνδυάζει, για πρώτη φορά, ιδέες από την *εξελικτική θεωρία παιγνίων* μαζί με αυτή της *αυτο-οργάνωσης* πολυ-πρακτορικών συστημάτων. Μοντελοποιούμε την εξέλιξη των κοινωνικών συμπεριφορών σε έναν πληθυσμό στρατηγικά αλληλεπιδρούντων πρακτόρων που συμμετέχουν σε επαναλαμβανόμενα παίγνια

με τα οποία ανταλλάσσουν πόρους (χρησιμότητα) με άλλους παίκτες. Η έκβαση των παιγνίων συμβάλλει τόσο στη συνεχή αναδιοργάνωση της κοινωνικής δομής των πρακτόρων, και στην προοδευτική υιοθέτηση των πιο επιτυχημένων στρατηγικών από τους πράκτορες. Ο αριθμός των πρακτόρων στο μοντέλο μας δεν είναι σταθερός, αλλά αλλάζει με την πάροδο του χρόνου, ενώ οι πράκτορες λαμβάνουν επίσης μη στατικές αποδόσεις, σε αντίθεση με τα περισσότερα παίγνια που μελετώνται στην βιβλιογραφία. Αυτό μας οδήγησε στην ανάγκη να παράσχουμε μια νέα διατύπωση της εξελικτικής δυναμικής των παιγνίων μέσω της εκτίμησης της (συνάρτησης) ωφέλειας των πρακτόρων και όχι των στρατηγικών.

Επιπλέον, το AncientS-ABM μπορεί να προσομοιώσει και *διακοινοτικές* αλληλεπιδράσεις, μοντελοποιώντας την ανταλλαγή και τη διανομή πόρων μεταξύ των διαφόρων κοινοτήτων πρακτόρων. Συγκεκριμένα, ενσωματώνουμε ένα υπο-μοντέλο εμπορικών συναλλαγών, χρησιμοποιώντας γνωστά *μοντέλα χωρικής αλληλεπίδρασης* για την προσομοίωση του εμπορίου μεταξύ των οικισμών, προκειμένου να εξεταστεί η αποτελεσματικότητα του εμπορικού δικτύου και της εξέλιξής του σε διαφορετικά χρονικά σημεία. Επίσης, χρησιμοποιώντας ιδέες από την *θεωρία γραφών*, αναλύουμε τη δομή του δικτύου εμπορικών συναλλαγών, επιδιώκοντας να κατανοήσουμε την κοινωνική οργάνωση της τεχνητής κοινωνίας σε υψηλότερο επίπεδο. Τέλος, επεκτείνουμε περαιτέρω το μοντέλο μας, ενσωματώνοντας ένα υπο-μοντέλο *φυσικής καταστροφής*.

Ως μελέτη περίπτωσης, χρησιμοποιούμε το μοντέλο μας για να αξιολογήσουμε τον αντίκτυπο συγκεκριμένων κοινωνικών οργανωτικών δομών σε μια τεχνητή 'Μινωική' κοινωνία της Πρώιμης Εποχής του Χαλκού στην Κρήτη. Η παραμετροποίηση του μοντέλου βασίζεται σε αρχαιολογικά στοιχεία και μελέτες, αλλά δεν προκαταλαμβάνει οποιαδήποτε συγκεκριμένη αρχαιολογική θεωρία ή παραδοχή. Αποτελέσματα από αρκετά διαφορετικά σενάρια προσομοίωσης καταδεικνύουν καλύτερη βιωσιμότητα για τους οικισμούς πρακτόρων που υιοθετούν ένα μοντέλο κοινωνικο-οικονομικής οργάνωσης που βασίζεται στην 'αυτο-οργάνωση', και όπου μια 'ετεραρχική' κοινωνική δομή αναδύεται. Τα αποτελέσματα δείχνουν επίσης ότι οι επιτυχημένες κοινωνίες πρακτόρων υιοθετούν μια εξελικτική προσέγγιση όπου η συνεργασία εμφανίζεται ως αναδυόμενη στρατηγική συμπεριφορά. Στα σενάρια προσομοίωσης όπου λήφθηκε υπόψη το υπο-μοντέλο φυσικής καταστροφής, παρατηρούμε αισθητές αλλαγές στην κατανομή των οικισμών, που σχετίζονται με σημαντικά υψηλότερα ποσοστά μετανάστευσης, αμέσως μετά την έκρηξη του ηφαιστείου της Θήρας. Επιπλέον, η αρχικά συνεργατική συμπεριφορά των πρακτόρων μετατρέπεται σε μια μη συνεργατική, παρέχοντας έτσι υποστήριξη σε αρχαιολογικές θεωρίες που υποδηλώνουν ότι η έκρηξη του ηφαιστείου της Θήρας οδήγησε στην κατάρρευση του Μινωικού κοινωνικο-οικονομικού συστήματος. Επίσης, φαίνεται πως η μοντελοποίηση ενός δικτύου εμπορικών συναλλαγών όπου ευνοείται περισσότερο η σημασία των οικισμών παρά η απόσταση μεταξύ τους, μπορεί να παράγει μοτίβα ανάπτυξης οικισμών παρόμοια με αυτά που υπάρχουν στο αρχαιολογικό αρχείο. Η ύπαρξη μερικών σημαντικών κέντρων διανομής πόρων, με ενδεχομένως ισχυρή ιεραρχία κατά την Πρώιμη και Μεσομινωική περίοδο, αλλά και σημαντικών κέντρων συγκέντρωσης πόρων κατά την διάρκεια της Ύστερομινωικής περιόδου, προκύπτουν επίσης ως εύλογες υποθέσεις μέσω της χρήσης του πρακτοροκεντρικού μας μοντέλου.

Examination Committee

Associate Professor Georgios Chalkiadakis (Supervisor), Technical University of Crete

Professor Euripides G. M. Petrakis, Technical University of Crete

Professor Apostolos Sarris, University of Cyprus

Professor Jan Driessen, Université catholique de Louvain

Professor Alexis Drogoul, Institut de Recherche pour la Développement

Professor Phaedon C. Kyriakidis, Cyprus University of Technology

Associate Professor Michail G. Lagoudakis, Technical University of Crete

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Chapter 1

Introduction

Archaeologists seek to interpret human (pre-)history by providing theories about the interactions between societies and their natural environment, grounded on archaeological evidence. This is accomplished via the use of formalisms and via the constant re-definition of objectives to be attained, questions to be asked and methods and techniques for answering them. Archaeological theories, however, are generally incomplete, in the sense that they are based on data that is static: it might reflect the results of the dynamic interactions among people, materials, monuments, landscapes, and the inhabited environment in general, but not these dynamics themselves. Thus, archaeology has a difficulty linking cause and effect in the past [127]. Apart from natural language, an alternative way to reason about historical and past actions and events from observed data, is to transform theoretical questions and hypotheses into computational terms; the aim is to find the means to explore possible answers. Towards this end, *computational modeling and simulation* can assist archaeologists on expressing individual or collective entities, relationships between them or phenomena, allowing them to explore and test theories against observed data, to conduct plausibility (or improbability) tests, and experiment with different sets of initial conditions and scenarios to explain particular sequences of cause and effect [45].

One of the pillars of computational modeling, essential for any simulation process, is of course mathematics, based on variables and their relationships. *Equation-based modeling* [10] is about defining a recurrence relation of given variables, once one or more initial values are given (difference/partial difference equations), or about relating some process or function with its derivative, *i.e.*, its rate of change (differential equations). For example, logistic or exponential growth equations describe population dynamics, while predator-prey equation models describe the dynamics in which two populations interact, one as a predator and the other as prey. Reaction-diffusion equations can describe the spread of populations in space, when two populations compete for a common food source ("competition"), or benefit from each other ("symbiosis"). Furthermore, *agent-based modeling* (ABM)[1] [140] is a field research methodology originally developed as part of computational modeling, but widely used by other disciplines, from life and physical sciences (biology, genetics, physics, chemistry) to environmental and social sciences (ecology, geosciences, demography, economics, sociology, archaeology). ABM is quite effective in representing the interactions among acting entities (agents), that may represent individuals, groups, societies or even nations, since these individual entities can be represented directly and can possess internal state(s), and a set of behaviours or rules that determine how the agent's state is updated from one time step to the next. Now, an equation-based modeling system is in general able to report similar behaviour in the results as an equivalent ABM [18]. Why then not use solely equation-based models rather than ABMs?

The major difference between these approaches is that the accuracy assessment of (real) observational data can be much better determined by an ABM, as it can adequately represent situations where small fluctuations in the input data can drive a system to a completely different state [18]. By contrast, equation-based systems would usually smooth out such effects, not allowing such out-of-the-norm situations to emerge. Moreover, though equation-based modeling variables allows saving and reusing data while

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

the model runs, ABM can incorporate complex agent variables which include both data and functionality at the same time. This results in an increased descriptive power that facilitates interdisciplinary research, as it allows the incorporation of concepts used in various disciplines (regardless of the discipline-specific "language" they were originally stated in). Such computational realization of conceptual processes can assist researchers in social sciences to model and simulate real world phenomena. It has to be understood, however, that ABMs must be run to test whether agents are behaving as their originators intended, and this has little or nothing to do with how well they might reproduce observable data [9]. This is not necessarily a drawback: *ABM models are not usually built for prediction per se, but (to a large extent) to feed structured debate and dialogue, and to provide a tool for apprehending and explaining certain underlying properties (cause and effect) of the world* [46]. Thus, in our view, the key objective of ABM is enriching our understanding of fundamental processes that appear in a variety of archaeological applications.

Scholars argue, however, that most agent-based simulation models used in archaeology and beyond simply do not define truly *autonomous* agents [43, 135], and ideas and notions from the Mutli-agent Systems (MAS) community and related principles that study the strategic behaviour of agents, such as game theory, should be followed in the design of the respective ABMs. This is something we attempted to do in this thesis, as will become apparent later.

The remainder of this introductory chapter underscores the motivations and questions which led us to explore research at the borderline of (computational) archaeology and ABM. It further outlines theoretical and methodological dimensions of the ABM in archaeological research and briefly outlines our novel model and tool, namely *AncientS-ABM*, that we provide for archaeological inquiry and in particular for the study of past human societies' organization. Finally, it concludes by highlighting the main research contributions of our work and gives an overview of the structure of this thesis.

1.1 The ABM and MAS approaches in Archaeology and Beyond

The study of social and environmental change is key to improving our current understanding of human behaviour and history. Nowadays, computer science and current information systems provide us with the opportunity to build virtual laboratories in which we can address various questions and hypotheses about such transitions. At the same time, knowledge of historic events that have actually occurred provides the possibility of interpreting the results, and evaluating the accuracy of specific computational models or simulations. Thus, it is only natural that, *computational archaeology* has emerged as the discipline that focuses on the study of ancient societies via the use of computer models and simulations [47]. Archaeology is a data-oriented discipline, with a strong focus on the collection of material information for the study of past human societies. Computational archaeology builds on this information in order to enhance our understanding of the long-term human behaviour and behavioural evolution, via modeling and simulating the socio-environmental processes at play. It utilizes mathematics, logic, or even cognition as the means for converting observations and knowledge about nature into quantalitative research; and scientific inquiry is used in order to produce, test, and confirm quantitative data and theories.

The concept of ABM has become very popular within (computational) archaeology over the last two decades [85]. Nowadays, ABMs can incorporate ideas from Artificial Intelligence (AI) [111] and Multi-agent Systems (MAS) [142], and define a social system as a collection of agents, which represent individual entities within a wider population. In MAS research, these entities are assumed to be acting autonomously, and may be able to learn and adapt in their environment. Agent actions occur in time and space, affecting the wider environment while individuals cooperate and/or compete with each other. ABMs can model systems that are either highly diverse or heterogeneous in terms of both agent abilities and underlying environment, and allow the study of interactions and (potentially emerging) behaviours that would be difficult to examine by using simple aggregate styles of representation [9]. ABM is particularly appealing as it promotes a style of modeling that reflects the characteristics of our real world, in a way that appears to fit well with existing explanations of how spatial structures such as settlements, cities, states, our global system and all its natural components evolve. The emerging popularity of ABM in social sciences, and in particular in (computational) archaeology, is largely due to its ability to represent individuals and societies, and to encompass the uncertainties inherent in archaeological theories or findings.

The major trends in recent archaeological simulation are mostly abstract ABMs intended to assist with hypothesis-generation and (to a lesser extent with) hypothesis-testing. Archaeology-related ABMs are mostly used to understand how certain processes work and what sort of changes could plausibly have occurred, rather than comparing the output of a simulated process against the archaeological evidence or record; however, the distinction between hypothesis-testing and theory-building simulation is not always so clear-cut in practice [85]. In addition, there are many formal systems competing or combining to provide their elements as theoretical and methodological dimensions for structuring ABM. Their relative value is determined by the questions that need to be answered in each particular situation [99]. In the remainder of this section, we describe the most important of such formal systems.

In most cases in archaeological research, scholars explore past processes that occurred in a given geographical landscape. An effective means for modeling is the coupling or integration of Geographical Information Systems (GIS) with ABMs when spatial and temporal design and analysis is required [31]. When one or more agent actions involves movement, when an agent's location within the environment influences its decision making, or when spatial arrangement of features on the landscape can be altered by the agents, then a geospatial ABM can better support the research requirements of the modeler. Moreover, in geospatial ABMs the importance of the spatial resolution is equally as important as the temporal resolution, where duration and frequency descriptive characteristics of events and phenomena are essential for temporal and spatial (pattern) analysis. Thus, when geographic context constitutes an important aspect of the conceptual model, the translated computational ABM needs to be coupled or linked with a GIS computational library, *e.g.* GeoTools (a Java GIS software library), Java Topology Suite (JTS), OpenMap, ESRI ArcObjects SDK, and others. Thereby several important functions of the ABM can be assisted, such as data acquisition, pre-processing or transformation, as well as determining and assessing various inputs and outputs when needed through spatial analysis tools (*e.g.*, density map, cost distance, least cost path, *etc.*).

ABMs can also be enhanced via the use of cellular automata (CA) to model complex systems. Von Neumann and Ulam introduced the concept of cellular automata in the 1940s [96]. CA is an insightful approach for building a system of many agents that have varying states over time. However, now agents are cells existing on a grid (a tessellation of n-dimensional Euclidean space), where each cell has a number of states and a neighbourhood which is a list of adjacent cells. Cell states evolve over a series of computational time steps; a cell's new state is a function of all the states in the cells neighbourhood at the previous time step, along with a set of simple rules for the cell to follow. Depending on the complexity, patterns may appear from simple specific rules, or the rules themselves can be classified as ones that evolve quickly into a stable state, into oscillating structures or into structures that interact in complex ways, and can be relevant to the study of biology, physics, social sciences and all fields of science [141]. Using CA within an ABM allows the conceptualization of a variety of real-world phenomena, where behavioural patterns are emerging out of the interactions among simple agents.

In a parallel direction, Von Neumann and Morgenstern invented the mathematical theory of games [131]. Since the 1970s, *game theory (GT)* became the main instrument for the analysis of the strategic interactions among rational agents, *i.e.*, entities that encompass preferences or goals and act upon them [95]. Agents can be also described by means of an abstract concept called *utility*, referring to some ranking or scale of the subjective welfare an agent derives from other agents in the game; while the aim of the rational agent is to maximize its expected utility payoff. GT aims to provide an explanatory account of strategic reasoning based on "rational" actions of agents, and thus to prescribe "optimal" strategic behaviour for use by agents in games. In situations where this is not the case, *i.e.*, when actions are not necessarily the results of rational deliberations by individual agents, but are rather "biologically" attached to particular strategies used by entire populations, then evolutionary game theory (EGT) can be of use [122]. EGT originated as an application of GT to biological contexts, arising from the realization that frequency-dependent "fitness" introduces a strategic aspect to evolution. Although EGT has been mostly applied in the context of evolutionary biology, it has also recently attracted the interest of social scientists, as "evolution" need not be strictly biological, but can be also understood as "cultural or social evolution". Since beliefs and norms change over time, EGT can help answer questions about the conditions under which language, concepts of justice, altruism, and other non-designed general social phenomena are likely to arise [121].

The above methodological dimensions can effectively structure an ABM, depending on the theories and hypotheses that need to be modeled. Nevertheless, MAS research has always been advocating that ABMs should be providing a higher level of abstraction than the one offered by object-oriented systems [75]. Modeled agents should be capable of autonomous action, and of maintaining high-level interactions and organizational relationships with other agents, while being potentially "selfish" [143]. However, most mutiagent-based simulation models used in archaeology, simply *do not* define agents in the way these are defined in AI or MAS research. Unfortunately, *"agents nowadays constitute a convenient model for representing autonomous entities, but they are not themselves autonomous in the resulting implementation of these models"* [43]. Most existing ABMs used in archaeology do not incorporate truly autonomous, nor utility-maximizing agents in their models. This is regrettable, as ABM can clearly benefit from the progress achieved in modeling (and employing) strategic decision-making in multi-agent worlds, which is the focus of MAS research in the past decades [135].

In this thesis, we present a functional ABM system prototype that we developed, called AncientS-ABM, consisting of agents that are completely autonomous, and can build and maintain complex social structures. Instead of a *simple reactive* agent architecture observed in most ABMs used in archaeology, a *utility-based* one is actually applied in our ABM.[2] AncientS-ABM is inspired by existing models and specific case studies, however, it is quite generic, can incorporate a number of different modules (submodels) regarding agent organization, their actions and interactions at both the agent and agent community level, and does not aim to prove or disprove a specific theory. We argue that, using agent-based models that were built on MAS principles and knowledge derived from archaeological research—but do not attempt to fit their results to a specific material culture—allows for the emergence of dynamics for different types of societies in different types of landscapes, and can help derive knowledge of socio-economic and socio-ecological systems that are applicable beyond a specific case study.

1.2 Contributions

In this thesis, we examine how methods and techniques from multiple computer science fields can be combined to deliver an augmented ABM to be effectively utilized in the archaeological domain. In order to establish an ABM that would actually simulate an artificial past society in a realistic landscape environment, one should examine many aspects, and most probably be called to utilize solutions from various fields of computer science or even other scientific fields. To the best of our knowledge, this is the first time that a formal agent-based modeling framework for simulating various social organization paradigms, pondered by available archaeological information, is provided in the literature. Specifically, we put forward AncientS-ABM, a fully-functional, generic, and modular ABM system that is easy-to-use by archaeologists, in the sense that it can

[2] Note that we do not mean to argue that utility is the main factor driving human behaviour or the advance of human societies. Nevertheless, utility theory have long been adopted as useful tool in the AI domain [111].

be employed for the study of practically any society of choice, can easily incorporate archaeological evidence or estimates, and can help test proposed archaeological theories or hypotheses regarding their social organization.

The core of our approach is to formally describe and improve agent-model design, as a means for developing simulations which can lead us to better understand emergent phenomena associated with the evolution of complex systems, such as artificial past societies organization. This is achieved by properly introducing and incorporating MAS ideas and techniques towards enhancing agent sophistication in organizational design. Importantly in this thesis we adopt and adapt a "self-organized" agent organization paradigm, where utility-based agents are autonomously organized into a "stratified" social structure, and continuously re-adapt the emergent structure, if required. In addition, we incorporate in our ABM a number of different social organization paradigms and subsistence regimes, along with an alternative evolutionary self-organization paradigm, inspired by EGT, where agents strategically interact with other agents in their community, with a view to study the evolution and adaptation of strategic behaviours of agents, and the effect these have on the artificial society as a whole. We further embody approaches and techniques from GIS, in order to properly capture spatial aspects of the realistic agent environment, agent-agent and agent-environment interactions. Last but not least, we also adopt methods from graph theory in order to adequately analyze these interactions at a network representation level. Thus, in this thesis we develop and present the AncientS-ABM framework, that is able to simulate agency and assess simulation results towards studying specific properties and patterns of archaeological information.

In Figure 1.1 we provide an overview of the scientific fields that we engaged in this research, highlighting the main contributions of this thesis towards utilizing agent-based modeling in archaeology with respect to these fields.

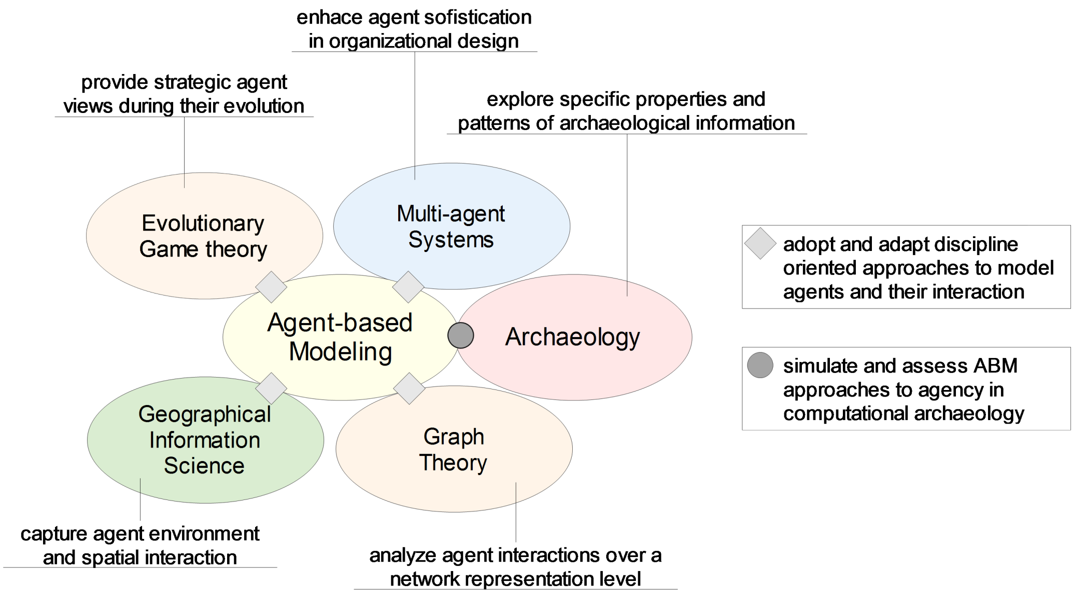


Figure 1.1: Overview of involved scientific fields and contributions of this thesis.

The main contributions of this thesis can thus be summarized as follows:

1. We showcase how MAS-originating concepts, techniques, and algorithms can be incorporated in an ABM, as such providing a stepping stone towards the aforementioned [135] ABM-MAS integration vision (Chapters 3– 6).

2. We provide a modeling approach that employs autonomous, utility-based agents (rational utility-maximizers) for modeling their intra-community interactions, unlike most existing ABMs in archaeology, which employ a simple reactive agent architecture. Our agents act autonomously towards utility maximization, and can build and maintain complex social structures (Chapter 3).

3. We incorporate in our ABM a social organization paradigm of agents *self-organizing* into a "stratified" social structure, and continuously re-adapting the emergent structure, if required. The self-organizing social paradigm builds on MAS work [81, 82] for problem-solving and task execution in modern self-organizing agent organizations. We note that this is the first time a self-organization approach is incorporated in an ABM system used in archaeology (Chapter 3).

4. We incorporate a number of additional social organization paradigms and different subsistence regimes (*e.g.*, cultivation systems) in our modeling approach, aiming to assess the influence of social organization on agents population growth, agent community numbers, sizes and distribution (Chapters 3 and 4).

5. We define a (somewhat sophisticated) agent decision-making process, which uses an Markov Decision Process (MDP) to decide on migration (or settlement) policies, and compare the viability in terms of population growth of the resulting agent societies against that of myopic agent action selection (Chapter 3).

6. We blend for the first time evolutionary game theory with multi-agent systems' self-organization for modeling the evolution of social behaviours in a population of strategically interacting agents. Specifically, we provide a novel evolutionary self-organization algorithm by simulating repeated "stage games" played by pairs of strategic agents, by means of which they exchange utility (corresponding to resources) with others. The results of the games contribute to both the continuous re-organization of the social structure, and the progressive adoption of the most successful agent strategies (Chapter 4).

7. We provide a novel model for our evolutionary self-organization approach, where strategy review and adoption, agent fitness, and the relative success of agents strategy are assessed and performed in various ways. In contrast to most (matrix) games studied in the game theory and MAS literature, our agents receive non-static payoffs, depending on their current utility, while the agent population is not constant, but fluctuates dynamically over time, due to utility-influenced births and deaths. These facts led us to provide a novel, alternative take on the classic fitness-based evolution strategy selection process (Chapter 4).

8. We conduct a systematic evaluation of the performance of various agent strategies, assuming several variations in the way agent fitness and agent organization fitness are defined, as well as in the way agents adopt new strategies, for studying the evo-

lution and adaptation of strategic behaviours of agents operating in the artificial communities, and the effect these have on the society as a whole (Chapter 4).

9. We incorporate a natural disaster sub-model (module) in our ABM, in order to assess the anticipated social crisis in terms of agents social structure adaptation, agent community numbers and sizes, migration behaviour and agents strategic behaviour evolution, before and after a natural catastrophe event; as well as to provide insights on how a natural disaster scenario could affect the trading network behaviour and further the agent communities organization structure (Chapters 5 and 6).

10. We provide a novel trading sub-model (module) that readily incorporates spatial interaction models to simulate agent inter-communities trading interactions. Moreover, we conduct a systematic evaluation of the agent communities trading network, aiming to explore the sustainability of agents and agent communities social organization by evaluating the effects of agent inter-community interactions. Moreover, we utilize graph theory to further interpret simulation results in terms of the network's potential centralization, clustering behaviour, or potential settlement hierarchy during the whole simulation period (Chapter 6).

11. As a case study, we employ our ABM to assess the *intra-settlement* and *inter-settlement* organization of "Minoan" agents affected by their interactions on agent and agent community levels, based on actual archaeological data and evidence (or estimates) on the Minoan civilization (Chapters 3 – 6).

12. We obtain intuitions, suggestions, and potentially provide support for existing archaeological theories. In particular, when agents adopt an "egalitarian" social organization behaviour, a settlement pattern of many "small-size" settlements is emerged, while when the self-organization social paradigm is adopted, a "heterarchical" social structure emerges, giving rise to fewer but larger settlements during the Middle – Late Minoan period. In addition, simulation results on inter-

settlement trading interactions suggest that a small number of influential centres could have existed during the end of the Early Minoan period, where resources are distributed by these centres to others in the network, with no clearly prominent settlement sites to which resources are directed. By contrast, the trading network connections are becoming much denser, and resources are being distributed towards only a few settlements in the network during the Late Minoan period and after the catastrophic event of the volcanic eruption of Thera, which appears to have led to a clear breakdown of the Minoan socio-economic system (Chapters 3 – 6).

AncientS-ABM is developed using the *NetLogo* multi-agent programmable modeling environment [139], and it is quite modular and generic and is easy-to-use by archaeology scientists. In fact, we followed a common design principle extensively adopted in the agent-based modeling community [4], known as K.I.S.S ("Keep it simple...and short"), including variables, constraints and mechanisms required to add to the quality of the model, while being also able to keep the system theoretically coherent and tractable in terms of results analysis and interpretation (cause and effect), as well as computation. Specifically, AncientS-ABM is currently supporting several modules and methods for its various modeling components, such as:

- migration and cultivation agent actions, with two different cultivation practices
- intra-community and inter-community agent interactions, with several social organization methods and spatial interaction methods respectively
- several topographical and archaeological spatial data layers, as well as a natural disaster module, currently supporting a volcanic eruption catastrophe, for the environment model

In Figure 1.2, we illustrate our ABM framework modularity, by providing a simple diagram of the various independent components and methods of the agent and environment models currently developed.

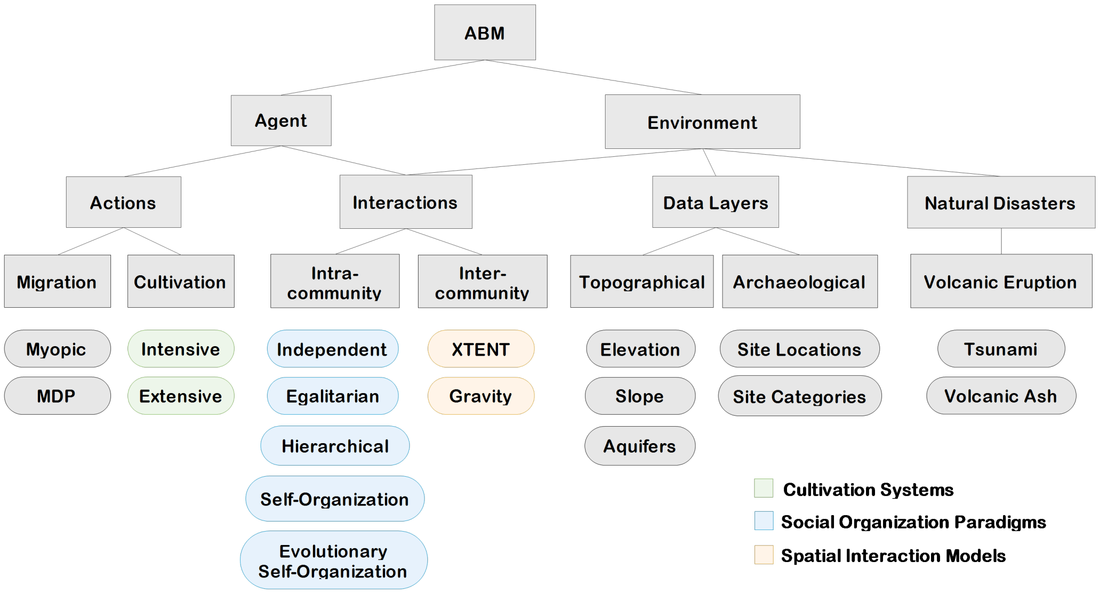


Figure 1.2: AncientS-ABM modularity diagram of the various modeling components and methods currently supported.

1.3 Thesis Outline

The structure of the rest of this thesis is as follows.

Chapter 2 discusses agency and organizational design through the prism of archaeology and computer science, along with an overview of ABM design methodology and existing examples of archaeology-related ABMs.

Chapter 3 presents our ABM, by describing the agent model, the model's environmental representation, agent intra-community interactions, and their various social organization-related characteristics. Most importantly, it describes the *self-organization* framework incorporated in this thesis; and presents an appropriate evaluation mechanism that measures the utility for agent re-organization decisions. We also present our specific case study of early Minoan societies, and record 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.

Chapter 4 extends our ABM framework by blending evolutionary game theory with multi-agent systems' self-organization. Our approach models the evolution of social behaviours in a population of strategically interacting agents (corresponding to households in the Minoan era). To this end, agents participate in repeated games by means of which they exchange utility (resources) with others. The games' outcomes contribute to both the continuous re-organization of the social structure, and the progressive adoption of the most successful strategies. We also present a systematic evaluation of the performance of the various strategies, assuming several variations in the way agent and organization fitness are defined, as well as in the way agents adopt new strategies. We note, that results demonstrate that strategic cooperation is in fact an emergent behaviour in contrast to the stage game equilibrium, and one that can better sustain and advance the agents' society (*e.g.*, higher population sizes are observed when agents cooperate).

Chapter 5 describes an additional module for out ABM system, incorporating a natural disaster sub-model. In particular, we enable the natural disaster sub-model during our simulations in order to evaluate the extent by which the cataclysmic volcanic eruption of Thera (Santorini) impacted the Minoan social evolution. To conceptualize the model, we considered simple processes based on archaeological estimates to model tsunami and volcanic ash impact on the artificial society and their effects on agriculture and human life. We also present an evaluation of the performance of different agent social organization paradigms, in terms of household agents sustainability, agent strategic behaviour, settlements' numbers and sizes, and migration rates during and after the volcanic eruption.

Chapter 6 presents a novel agent-based trading module in our ABM framework, for simulating the exchange and distribution of resources across (agent) settlements in past societies, that can employ any spatial interaction model of choice. We enable the trading sub-model to study the settlements' trading ability and power, given their geolocation and their position within the trading network, and the structural properties of the network itself, using as a case study the Minoan society during the Bronze Age, in the wider area of “Knossos” at the island of Crete, Greece. Two well-known spatial interaction models, XTENT and Gravity, are described, adapted and employed for conducting a systematic evaluation of the dynamic trading network that is formed over time. We also present and interpret our simulation results, assessing the sustainability of the artificial Minoan society in terms of population size, number and distribution of agent communities, with respect to the available archaeological data and spatial interaction model employed. We further evaluate the resulting trading network's structure (centrality, clustering, etc.) and show how it affects inter-settlement organization, providing in the process insights and support for archaeological hypotheses on the settlement organization in place at the time.

Finally, Chapter 7 concludes this thesis and discusses future research directions.

Chapter 2

Background

In this chapter we provide some background on important concepts and approaches relevant to our research. Specifically, we discuss notions linked to the understanding of the social organization of a given society, as appear in archaeology and MAS research. We also provide an overview of agent-based modeling and its design methodology. Moreover, we brief review existing ABMs used in archaeology research; and present a very basic background on the Minoan civilization and its social organization, as this is our case study in this thesis.

2.1 Archaeology and Social Organization

Social Archaelogy [107] 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 [118, 107]: *Bands*, small-scale societies of hunters and gatherers, fewer than 100 people, who move seasonally to exploit resources, and lack of 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 subsistence is based on cultivation and livestock, 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 be 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 show a characteristic urban settlement pattern, and often a pronounced settlement hierarchy exists—with a capital city as a major center, and several regional centers and villages that were peripheral to that city.

There are sufficiently marked differences between simple and more complex societies, as increased specialization and intensification takes place among different aspects of their culture. Nevertheless, the classification system above can admit a given society into more than one categories. It is far from clear, however, that one should assume societies evolve from bands to segmentary societies, or from chiefdoms to states [107].

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 [118, 107]. 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 [107]. 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 multi-agent systems research can potentially offer a helping hand.

2.2 Multi-agent Systems and Agent Organization

Multi-agent system approaches towards organizational design can be considered to be either agent-centric or organization-centric [86]. 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 [37], OMNI [129], Norms based [88], ODML [68], KB-OR [120]), 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 [36] 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. They argue that 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 multi-agent 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 [35]. 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 [81, 82], adaptation targets organization-wide characteristics, such as *structure*, rather than the individual agent ones. 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 [36]. 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 Section 3.2 we present in detail a self-organization method developed in this thesis, one which adopts aspects of and builds on the approach of [81, 82] mentioned above.

2.3 ABM Design Methodology

Agent-based computational experiments simulate the simultaneous (synchronous or asynchronous) operations and interactions of multiple agents, where complex phenomena may emerge, combining ideas and approaches from formal systems discussed previously in Section 1.1. The entire process of building an ABM begins with a conceptual model, where the main questions or hypotheses of the researcher solidify model elements (*i.e.* agent entities), with their attribute characteristics, behavioural and interaction mechanisms among themselves, and the model environment. In this section, we discuss the design methodology and available architecture for these elements, as well as a way of making model descriptions more understandable and complete. Moreover, for a beginner or non-expert in computer programing, there are several modeling system tools available to assist the development of an ABM. The subsequent subsections identify several ABM toolkits widely available and key model design considerations.

2.3.1 Modeling toolkits

Any ABM can be implemented with any object-oriented programing (OOP) language, since it is developed as a computer program. The concept of "object" in the computer programming paradigm, is used to describe (perhaps inadequately) data structures that contain data (fields or attributes) and functions (procedures or methods) that can access and modify their own data. Thus, the most suitable way to develop ABMs is if we consider objects as agents. An experienced modeler in OOP can build an ABM from scratch; however, there are several advantages to utilizing existing modeling tools for ABM development. Such benefits include reduced time for programming non-specific parts, *e.g.* data import/export, graphical user interface (GUI), etc., or the inbuilt implementation of various procedures, routines or methods needed. Although there are many toolkits for developing ABMs, we present here just a few of them, selected because they have up to date active maintenance and development, are widely used with a large user community, model libraries, tutorials and documentation, and being also able to be integrated with GIS extension libraries for geospatial ABM development. However, it is important for the modeler to always select software based on their purpose, design objectives and modeling capabilities.

NetLogo[1] [125] is highly recommended for modelers with beginner-level programming skills. It is a multi-agent modeling environment for simulating natural and social phenomena, has been in continuous development since 1999, and is capable of modeling relatively complex systems. NetLogo is simple enough for both students and teachers, yet advanced enough to serve as a powerful tool for researchers in many fields. It has an extensive documentation, many online tutorials, with a large model library of collected pre-written ABM simulations, addressing research areas for almost every discipline, as well as several useful extensions, such as GIS and Networks. NetLogo is an open source software library and runs on the Java virtual machine, thus it also constitutes a cross-platform modeling toolkit, while its computer programming language is the Logo dialect, a programming language designed specifically for ABM.

The Repast Suite[2] [100] is a family of advanced, free, and open source ABM and simulation platforms that have collectively been under continuous development for more than a decade. It is perhaps the most actively maintained solution for ABM with a large user community. Repast comes in two editions; the Repast Symphony edition, which can be used when the modelers' programming background is limited or when the modeler needs to use rapid prototyping to quickly develop an ABM (using ReLogo or Java); and the Repast HPC (Repast for high-performance computing), when the modeler needs to develop a model of a complex system with a large number of agent interactions and is also familiar with the C++. The Repast suite provides visual and easy to use capabilities for agent design, behaviour specification, model execution, and results examination. The modeler may also specify spatial elements of the model (e.g., geographic maps or networks) and different types of agents with specified behaviours.

[1] See http://ccl.northwestern.edu/netlogo.
[2] See https://repast.github.io.

MASON[3] [87] is a multi-agent simulation modeling tool designed to support a large numbers of agents relatively efficiently on a single machine; it has no capabilities for distributing models over multiple computers, although an extension for this (D-MASON) is available. MASON has no domain-specific features unlike the previous toolkits and it is highly modular and consistent, allowing the modeler to use and recombine different parts of the system. Moreover, it has a large set of utilities to support model design as well as several valuable extension packages for geospatial support, for social network systems analysis, as well as a high performance evolutionary computation system to discover design solutions for complex ABMs. Thus, a working knowledge of Java is a requirement for the modeler in order to use MASON.

GAMA[4] [123] is a modeling and simulation development environment for building spatially explicit agent-based simulations. It is also an open source application software based on the architecture provided by Eclipse[5], where users can undertake most of the activities related to modeling and simulation, such as editing models and simulating, visualizing and exploring them using dedicated tools. GAMA is a cross-platform modeling toolkit, while its computer programming language is GAML, a programming language designed specifically for the platform. There is also an extensive documentation and tutorials designed to ease the first contact with it, by identifying tasks of interest to modelers and how they can be accomplished within GAMA. Currently, GAMA offers advanced visualization features (*i.e.*, different displays composed of several layers, enhanced 3D visualization) [55] and also has several new features that enables the platform to simplify the work in participatory modeling and simulation, allowing human participants to interact with a simulated environment [124].

[3] See https://cs.gmu.edu/ eclab/projects/mason.
[4] See http://gama-platform.org.
[5] See https://www.eclipse.org.

2.3.2 Agents, environment and interaction topologies

A typical agent-based model has the following essential features: a set of agents with their attributes and behaviours, a framework for simulating agents in which they interact with their environment in addition to other agents and a set of agent relationships, and methods of interaction in which an underlying topology of connectedness defines how and with whom agents interact, as shown in Figure 2.1.

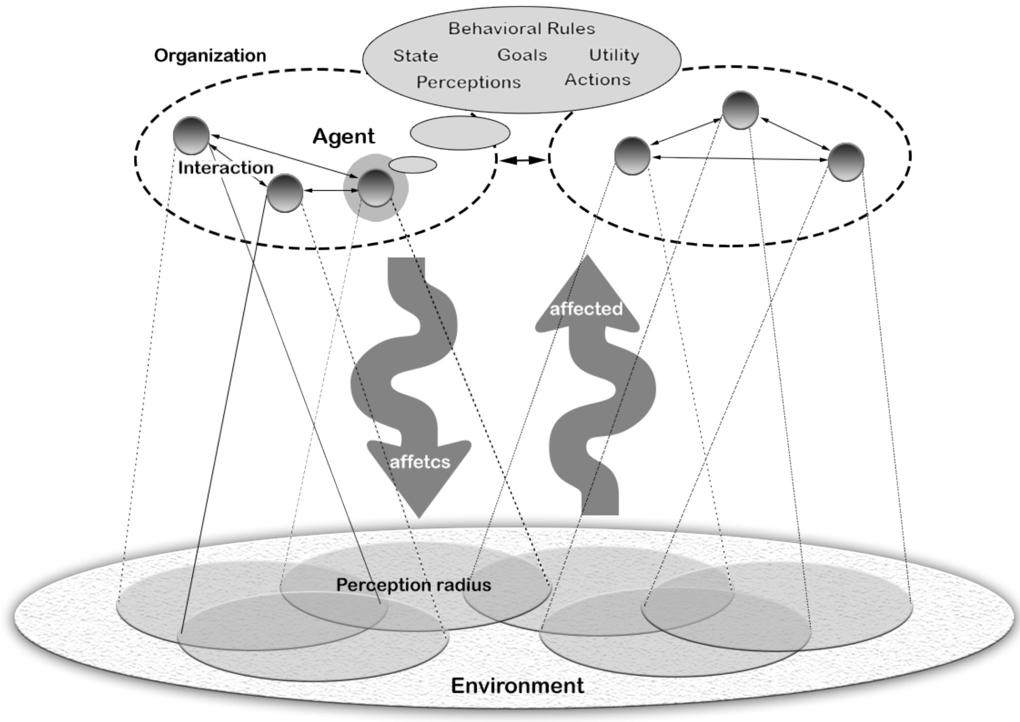


Figure 2.1: Virtual structural framework of a typical ABM (*adapted from Jennings 2000*)

While ABM originates from computer science as a computational modeling approach, the interdisciplinary nature of ABM may not allow a universally accepted definition of the term agent. Nonetheless, one of the most widely accepted definitions of an agent is provided by Jennings [75]; an agent is a software-based computer system, situated in some environment, and which is capable of autonomous action in order to meet its design objectives. Several agenthood properties that come from the above definition, such as the following:

autonomy agents are actual problem-solving entities, and have (at least some kind of) control over their choice of actions and behaviours—*i.e.*, they rely on their own percepts and deliberations for decision making, and are capable of processing (and exchanging) information in order to make independent decisions,

heterogeneity agents can be heterogeneous with different attributes and characteristics which may differ in several ways (*e.g.* preferences or behaviours), and over time,

pro-activeness an agent can exhibit goal-directed behaviour,

re-activeness an agent is able to perceive and respond (act) within its environment,

social ability an agent can be interactive or communicative, being able to share or exchange information with others, and act within a given social environment.

However, agents can possess other properties and depending on the application, some of their features will be more important than others. Thus, the above list is not exhaustive or exclusive. Along with agent behavioural characteristics, the structural design of the agent needs to be described. The appropriate structure of the agent depends on the nature of the environment modeled. An agent can operate in an environment that has various properties that influence its behaviour as well as its structural design. Thus, before designing an agent, the first step is to always specify the environment in which agents will act, as fully as possible.

According to Russel and Norvig [111], agent structures and environments vary along several significant dimensions. Agent environments can be organized according to their properties like:

fully or partially observable where the agent is either able or unable to gather complete information about the environment,

deterministic or stochastic when only agent actions, along with the current state of the environment, are able or not to determine the environment's next state,

static or dynamic when the agent is the only entity that brings changes on the environment or when changes in the environment happen while the agent is acting,

discrete or continuous when possible environmental states are finite or not.

Finally, an environment can be obviously single-agent or multi-agent; the later can be also seen as a competitive or cooperative one, depending on the situation. A simple case scenario of an ABM environment would be a fully observable, deterministic, static single agent environment. Perhaps in such an occasion designing the simplest agent structure could be sufficient, a reactive (or simple reflex) agent. These agents select actions based on their current perception of the environment, ignoring previous perceptions history. They are based on simple condition-action or *if-then-else* rules—*i.e.*, providing immediate (reflexive) responses to perceptions. Although such an agent design has a low demand on computational power, the resulting agents are of very limited sophistication or intelligence. For complex settings, however, a deliberative or rational (or intelligent) agent needs to be designed. Such an agent is able to store previous perception history, use an internal model, employ some goal information for its decision making or use a *utility* function to evaluate how close to its goal the agent is, rather than simply perceive whether a goal has been achieved or not—and then choose an action.

Now, agent perception (within a sphere of visibility and influence) and action capabilities determine its nature of interaction with the environment and other agents. What is more, when agents interact there is typically some underlying organizational context, representing the nature of the relationships among the agents. Thus, the possibility of specific agent *interaction topologies* might need to be taken into account prior to model design [89], as show in Figure 2.2.

The choice of an agent interaction topology very much depends on the modeler's needs. For instance, a grid or lattice interaction topology can be used when an agent need to be represented either as a grid's cell (cellular automata) or as an entity situated in a grid cell, where Von Neumann or Moore neighborhoods can be further taken into

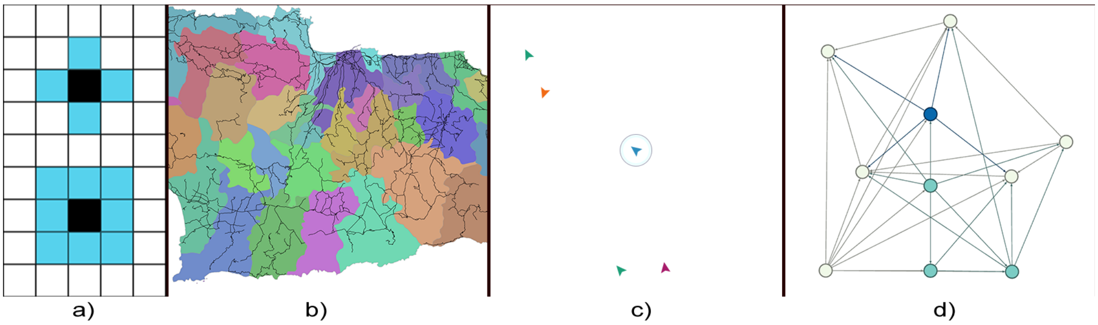


Figure 2.2: Potential agent interaction topologies for a computational ABM (*adapted from Macal and North 2009*)

account (Figure 2.2a).[6] Likewise, a polygonal tilling scheme (employing polylines as well) can be used when a realistic GIS map need to represent the environmental framework of the model (Figure 2.2b). When the modeler needs the agents to be able to move and interact within a simple representation of physical space, then the environment can be represented as an Euclidean 2D (or even (3D) continuous space (Figure 2.2c). Finally, a network interaction topology can be used for representing (weighted) connections between the agents (nodes) where both directed and undirected relationships (links or edges) may exist.

There are several other common structural conventions that may also exist in most ABM implementations [99]: a *logging mechanism*, used to record different parameter values during model simulation runs for later analysis; a *scheduler*, responsible for representing the temporal aspect of a simulation, *i.e.*, it can be a "time stepped" scheduler, where agent actions or events (procedure calls) occur in each time (period) increment, or a "discrete event" scheduler, where several actions or events need to be executed at a specific time (duration). An optional Graphical User Interface (GUI) is also always included to facilitate the modeler during the ABM implementation, initialization and simulation stage. Apart from these elements, it may also be necessary to provide a formal description for an ABM, both for assessing the model design and the dissemination of the researcher's work, as explained in the next section.

[6]We note that, a triangular, hexagonal, etc. tessellation can be of use instead of a rectangular one.

2.3.3 Formalizing model design

Building a computational model from an informal theory is not a trivial matter, while formal theories are often too wide-ranging to put into computational terms. Therefore, it is necessary to reduce them to a few selected features which contain the essence of what is being described. To this end, the ODD (Overview, Design concepts, Details) protocol was developed as a standard format for describing ABMs [56]. ODD provides a general structure for formulating ABMs by describing models using a three-part approach involving: (i) an *overview* of the model, (ii) important *design* concepts, and (iii) specific *details*. Model overview includes a statement of the model's purpose, a description of the main entities, variables or attributes, temporal and spatial resolution of the model, and a discussion of the agent activities. Model design concepts include a detailed description on how abstract notions of the model, such as objectives, interaction, adaptation, stochasticity, observation, a.o have been taken into account and represented in computational terms. Finally, model details include specific elements regarding the initial setup configuration, input value definitions, and descriptions of the ABM.

Other modeling aspects, such as calibration (or sensitivity analysis), verification, and validation can be part of the ABM methodology. Indeed, depending on the case study, a modeler may calibrate an ABM to specific historical cases, if there is enough supporting data (deductive reasoning), or sweep a range of parameters over several possible scenarios to identify important thresholds or reveal tradeoffs and inherent uncertainties. ABM simulations must be reproducible (defining random seeds for the incorporated pseudo random number sequence generator); but even if they are not, a modeler needs to run a high number of simulations and examine aggregated parameter values, rather than being satisfied using just one single run of the model. The true power of the ABM approach is that one can rigorously incorporate in the model specific research findings within any given domain, *e.g.* biology, physics, geography, archaeology, sociology, etc. This ability brings out the true interdisciplinary nature of ABMs. Thus, it is essential to understand that ABMs are meant to test whether they are behaving as their modelers intended, and not to prove or disprove any specific theory or hypothesis; however, certain simulation results can potentially provide support or gain new insights to existing theories.

2.4 Related Work: Archaeology-related ABMs

In recent decades, archaeologists have used agent-based models to test possible explanations for the rise and fall of 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 [79]. The model results show the importance of environmental factors related to water availability for these settlement changes. However, results for 30 different (parametarisation) scenarios of just one run are presented. Moreover, as in most of the existing models, agents actions in the model are mainly cultivation/farming and migration, not based upon utility maximisation but rather on threshold rules. Finally, agents do not interact with each other but act independently.[7]

A similar (quite well-known) ABM study involved the cause of the collapse of the Anasazi, around 1,300 CE in Arizona, USA [34, 6]. 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, the authors of [34] refute the hypothesis that environmental factors alone account for the collapse. Agents in the Anasazi model (of the same environmental area with the work of [79]), however, once again do not interact with each other. Agents are *simple reactive* (*i.e.*, incorporate simple condition-action rules [111]), 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 1,300 BC [57]. A further cause of concern regarding the model's accuracy and fairness is that in [6] the authors apparently calibrated the model by mini-

[7]Mortality and fertility rates in [79] depend on the agents' "age", rather than on production.

mizing the difference of the simulated and historical data, using only 15 simulations, and published the best fit, notwithstanding the apparent great variation in their results [73]. As a result, neither are the agents in the ABM truly autonomous, nor the hypothesis being studied was appropriately evaluated in that line of work.

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 [38]. 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 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 simulating a given society [30], this is not mentioned at all in [38].

Archaeologists are now beginning to make use of spatial information in their models, through data provided by Geographical Information Systems (GIS). Models like the *CybErosion* 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 [132]. 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 [28] 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.

MayaSim [65] is a 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 the Maya social-ecological system, and to test quantitative indicators of resilience as predictors of the system's sustainability or decline. 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 utility-based agents, representing *Maya settlements*, to develop and expand within a landscape that changes under climate variation and responds to anthropogenic pressure . Settlement agents may migrate when population levels decrease below a certain threshold required to maintain subsistence agriculture. Agent utility function combines weighted functions for agriculture, ecosystem services, and trade benefit, affected by resource exchange that occur between settlement agents, that 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 nearby agents within a "Moore neighbourhood" cells (spatial ties). However, agent decisions are hard-coded in the model *e.g.*, migration or adding new and degrading existing trade route links between the agents are based on threshold rules, thus compromising agent autonomy. Model results suggest that the demise of a globally significant settlement node could result in cascading failure in the whole trading network, while the model itself requires refinement and further calibration in order to be able to reproduce spatial patterns somewhat analogous to that of the ancient Maya.

The above model essentially constitutes one of the two models we are aware of that include utility-based agents. The second model we are aware of and can be considered utility-based, is an ABM aiming to understand the possible mechanisms underlying periods of aggregation and disaggregation of prehistoric societies in arid environments, not aiming to represent a specific case study [74]. Agents in the ABM represent households making decisions about resource use and migration. Moreover, one or more agents in an environmental cell represents a settlement, which may exchange resources with other settlements based on conditional rules. The ABM could explore to some extent how various assumptions concerning social processes, such as migration, storage, and exchange affect the population aggregation and size, and the dispersion of settlements in a spatially explicit landscape with rainfall variability. Agent interactions in that simple model, however, are largely determined by rules that are built in the system. Our ABM presented in this thesis shares several basic features with that of [74], but is also in many ways distinct to that model, as we will be detailing in Section 3.1.5.

In summary, ABMs nowdays can integrate geospatial information along with archaeological evidence, and help researchers gain a better understanding of ancient societies evolution and environmental processes. However, as it is already understood, 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 have a rather vague idea about what is really allowed or not for defining such models in computational terms [43]. Thus, essential agent features such as *autonomy* or *interaction ability* 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 need 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. Moreover, there is an apparent 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. Our ABM system presented in this thesis is such an open one, and can incorporate self-organization mechanisms that allow for flexible agent interactions and the dynamic modification of organizational characteristics.

2.5 The Minoans and their Social Organization

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.[8] 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 [63]. 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 [30].

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.[9] Unlike what was the case in the Mellars model of the EOS project [38] (see Section 2.4), the wealth of environmental resources sustaining the Minoan civilization is not our focus of attention here. Archaeological evidence strongly suggests that the Minoans were agriculturalists and pastoralists [66], as well as traders, and their cultural contacts reached far beyond the island of Crete—from Greece to Egypt to Anatolia [70]. 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

[8]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 [138], 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 [92].

[9]cf. Table A.1 in Appendix A for the conventional chronology dates (BCE) of the Minoan period used in our ABM simulation scenarios.

conflict, functionalism, interactionism, etc.) that may be suggested for the Minoans' social organization and subsistence [29]. Archaeologists still struggle to find if there are any signs of a settlement hierarchy in the Pre-palatial (early Middle Minoan) 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) [116]. In [106, 108], the authors argue that interactions between different socio-political 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 [15].

Moreover, a series of changes in the Aegean, in particular in the Minoan society, were triggered by the LM (Late Minoan) IA or *ca.* 16th c. BCE Santorini eruption [42]. These changes would have caused the breakdown of the Minoan system over the course of a few generations, during LM IB (15th c. BCE). Archaeologists hypothesize that the eruption would have initially caused major problems in food production and distribution, undermining central authority and leading to a process of decentralization; this fragmentation would then have led incrementally to internal conflict. However, despite the many destructions and abandonments documented, Minoan culture survived.

There is still no agreement on the absolute date of the eruption. Quite a few earth scientists take the late 17th c. BCE date (between 1630 and 1600 BCE) for granted, whereas many archaeologists remain to the traditional late 16th c. BCE date, roughly around 1530-1520 BCE [40]. Despite the absolute date of the eruption, there is little doubt that the eruption was preceded and probably even triggered by one or more earthquakes. However, considering the archaeological record of Bronze Age Crete, careful analysis of old and new archaeological data suggest that earthquake evidence is patchy, frequently ambiguous, and generally less spectacular than what popular accounts of Minoan society would expect [78]. Regardless, the Theran eruption continues to trouble scientists, especially on questions surrounding the volcanic eruption absolute date and its impact on the ecosystem of the Ancient Mediterranean.

Chapter 3

AncientS-ABM: Simulating Ancient Societies

In this chapter we describe in detail the core of a functional ABM system prototype for simulating an artificial ancient society of agents. We focus on using autonomous utility-maximizing agents for studying historical social dynamics and evaluating the impact of different social organization paradigms on the artificial past society, in terms of population sustainability and agent community sizes for various simulation scenarios. Importantly, the model incorporates a social organization paradigm of agents *self-organizing* into a “stratified” social structure, and continuously re-adapting the emergent structure, if required. As a case study, we consider an artificial Early Bronze Age “Minoan” society residing at the wider area of *Malia* at the island of Crete during the Bronze Age; model parameter choices are based on archaeological evidence and studies, but are not biased towards any specific assumption.

Simulation results demonstrate that self-organized agent populations are the most successful, growing larger than agents 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"* societies, provides support for so-called *"managerial"* archaeological theories which assume the existence of different social strata in 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 [19, 52].

Our work here provides several contributions, also illustrated in Figure 3.1 below:

- We present a complete ABM framework that incorporates MAS-originating concepts, techniques, and algorithms. In particular, we employ autonomous, utility-based agents (rational utility-maximizers) for modeling their intra-community interactions, unlike most existing ABMs in archaeology, which employ a simple reactive agent architecture.
- We incorporate a number of different social organization paradigms and subsistence regimes (*e.g.*, cultivation systems) in our modeling approach.
- We conduct a systematic evaluation of the influence of the various social organization paradigms on agents population growth, agent community numbers, sizes and distribution.
- We specifically incorporate a social organization paradigm of agents *self-organizing* into a "stratified" social structure, and continuously re-adapting the emergent structure, if required. We note that, this is the first time that a self-organization approach is incorporated in an ABM system used in archaeology.
- We also define an (intelligent) agent decision-making process, which uses an MDP to decide on migration (or settlement) policies, and compare the viability in terms of population growth of the resulting agent societies against that of myopic agent action selection.
- As a case study, we employ our ABM to assess the intra-settlement organization of Minoan agents affected by their interactions, based on actual archaeological data and evidence on the area and period under study.

As such, in this chapter we put forward AncientS-ABM, a modular and generic ABM system, that is easy-to-use by archaeologists, and can easily incorporate archaeological evidence or estimates to help them test proposed archaeological theories or hypotheses regarding their social organization.

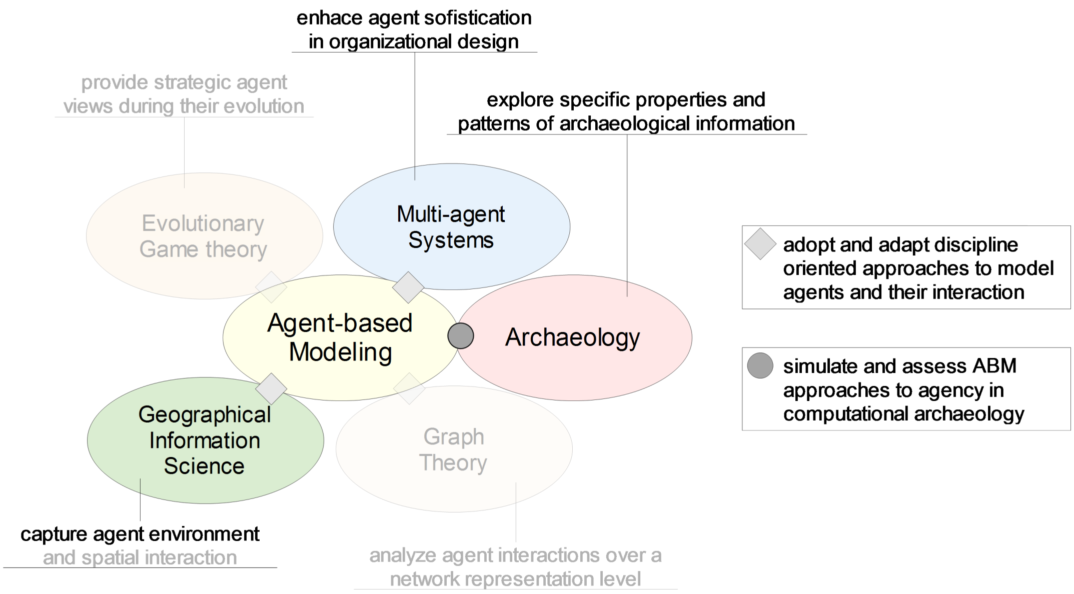


Figure 3.1: Overview of involved scientific fields and contributions in Chapter 3.

The remainder of this chapter is structured as follows. Section 3.1 presents our model, by describing its environmental representation, its agents, their actions and interactions. Section 3.2 describes various social organization paradigms and related characteristics. Specifically, it presents the self-organization algorithm incorporated in this work and an appropriate evaluation mechanism that measures the utility for agent reorganization decisions. Following that, Section 3.3 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, Section 3.5 provides an interpretation overview of our simulations and concludes this work. Parts of the research described in this chapter appeared originally in [114], [20], [21], [26] and [22].

3.1 A Utility-Based Multi-agent Model

Agents in our ABM correspond to *households*, which are considered to be the main social unit of production for the area and period under study [137], 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 *one year*, household agent 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 it also leads to overexploitation of resources, or to less nearby area available for cultivation, or higher transportation cost to further away areas cultivation, and thus, (implicitly) induce a lower crop yield. 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 main processes is presented in Figure 3.2. The arrows in the figure show how one process affect another in the MAS simulation model.

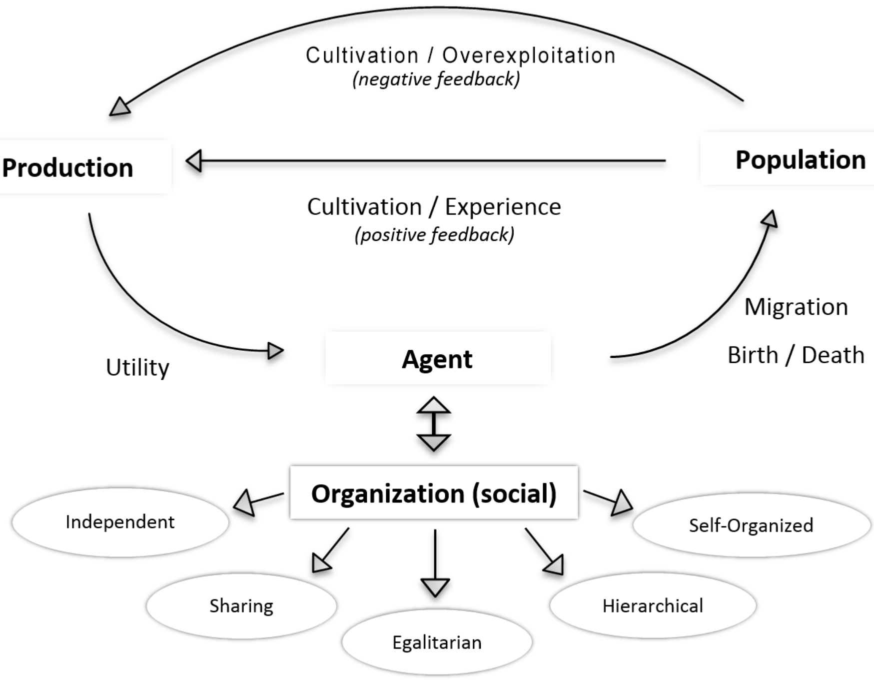


Figure 3.2: The ABM main processes interaction

The ABM allows us to explore the use of different cultivation systems that could be used by the agents, and thus test their impact on population size and dispersion and society's viability. At its current implementation, it allows the use of two agricultural practices: *intensive farming* ("garden" cultivation with hand tillage, manuring, weeding, and watering) and *extensive agriculture* (large-scale tillage by ox-drawn ards)[1] Additionally, our 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.

[1]These are the agricultural practices in use at the period of interest for our case study here [60, 71].

3.1.1 Model environment and resources

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

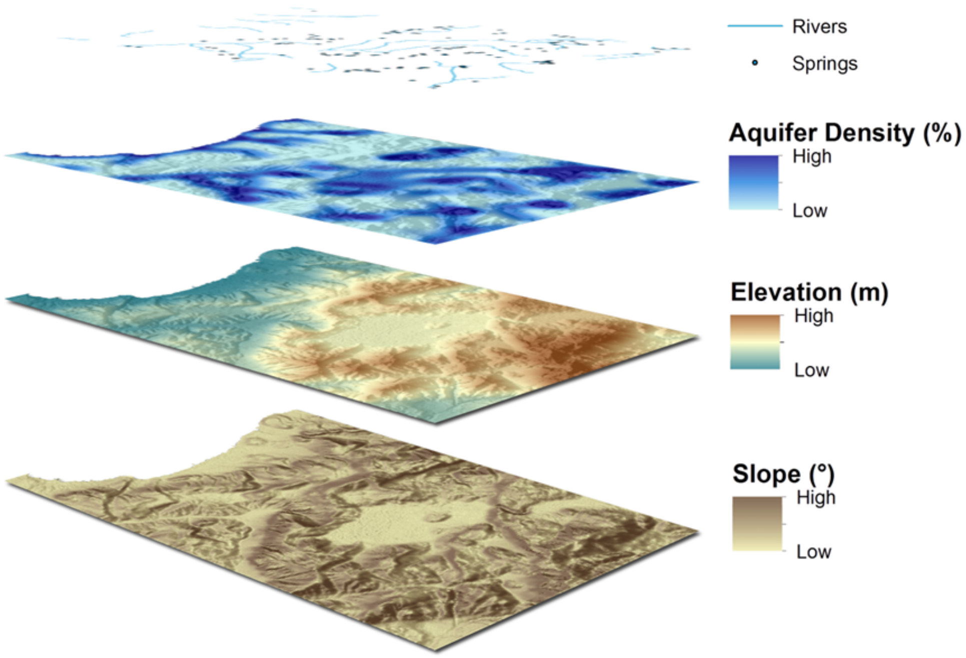


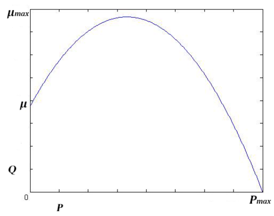
Figure 3.3: Environmental data layers of the ABM

The ABM environment can be classified as accessible, non-deterministic, since there is uncertainty about the outcome of a particular action (cultivating, migrating), dynamic and discrete (as discussed in Section 2.3.2). The environment has also various data layers (see Figure 3.3) 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 current data and are concerning the topography, which is today's Digital Elevation Model (DEM), slope and aquifer locations, such as rivers and springs.

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 environmental 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 yield is reduced, due to overharvesting (overexploitation).

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

$$Q_i\left(P\right) = \alpha_i \left(\frac{2\mu - 4\mu_{max}}{{P_{max}}^2} P^2 + \frac{4\mu_{max} - 3\mu}{P_{max}} P + \mu \right) \tag{3.1}$$



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)[2], 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 population size per cell, 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. We assume that there are no agricultural activities in areas with slope more than 45^o (this is actually a generous assumption, especially considering the era being modeled). Thus, α_i is used to represent the decay

[2] In Equation 3.1 we use the agents organization population per cell P influence the amount of labour applied on a cultivating cell, even though any given cell contributes to the utility of a single agent only (*cf.* Equation 3.3), since field cultivation was in many respects communal in those times [126]. Regardless of that assumption's validity, this value is essentially "normalized" by the maximum possible population per cell; thus the Q_i function's desired behaviour would have been entirely similar had we used the household size instead of the settlement population. Moreover, this function is used by all competing social organization paradigms in our experiments, thus granting none of them an unfair advantage.

of agricultural land suitability with increasing slope.[3]

Equation 3.1 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 overexploitation). It was inspired by the logistic map equation, the discrete version of the logistic differential equation, widely used to model population growth [130]. In our simulations, a cell's initial production output Q_i at a given run (corresponding to period of 2,000 years) is multiplied with a sample from a standard normal distribution, and thus varies across runs.

3.1.2 Agents and their actions

Households are *utility-based autonomous* agents who they can settle (or occasionally re-settle) and cultivate the land in a specific environmental location. They also possess an explicit representation of the environmental grid (perception radius), and use this to choose the best available migration location they can move to, in order to improve their utility. Thus, the actual agents 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 their actions (e.g., choosing a migration location, or asking others for help) seek to maximise the expected value of a given utility function—even though, at its current implementation, this utility function is rather myopic.

The main preoccupation of the agents is to *stay alive* by acquiring and consuming resources harvested from the land. If an agent household fails to acquire enough energy it will eventually die out, since it will stop procreating, as explained in Sec. 3.1.3 below. Acquiring energy is the only inbuilt goal of the agents. Thus, at every time step, the agents seek to pick the action b' that appears to be most rewarding in terms of producing

[3] We do not take into account "terracing", a type of farming at sloped planes that have been cut into a series of successively receding flat surface, which resemble steps.

resources at a given time step:

$$b' = argmax_{b \in E_x} U_x(b) \tag{3.2}$$

where E_x is the set of all energy-generating actions for agent x in the model.

In the case study considered here, agents acquire energy only via harvesting the lands. Therefore, the (expected) utility U_x of the agent x is simply described as follows:

$$U_x = \max\{\sum_{\mathrm{k=1}}^{n} Q_k, U'_x\} \tag{3.3}$$

Equation 3.3 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). The number of cells n, that a given agent x is able to cultivate at a given position, depends on its size and the cultivation system in use, as we detail below.

An agent x needs to be receiving some minimum utility from its cultivated cells, in order to be fit enough to procreate (see Sec. 3.1.3). The minimum utility (minimum level of resources) for household agent x containing j individuals is calculated as:

$$U_x^{thres} = j \times res_{min} \tag{3.4}$$

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 y years. 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 [71]. Therefore, agents in our current implementation, decide, on a yearly basis, to cultivate only the number of cells deemed necessary in order to sustain themselves for another year. The number of cells n that a household agent x is able to cultivate are thus calculated by dividing the minimum level of resources U_x^{thres} with the (maximum) harvest amount per cell, provided by the agricultural regime in use (*cf.* Section 3.1.4 below). 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.

Action: Migration. If agent x does not receive the minimum level of resources it requires, U_x^{thres}, for y years in a row (and its storage is empty), it considers migrating to another location or settlement. At time step t, agent x calculates its expected utility U'_x for the new location at time step $t+1$, as the average *reward* of the neighbouring cells which is defined by Equation 3.1, considering the agent moved to the respective *unused* cell (*i.e.*, a cell that does not correspond to cultivated land from any other agent). The unused cell might lie within another established settlement; in that case, agent x first considers the average expected utility of agents in the settlement in question. In both occasions, if the agent's expected utility U'_x for the new location is higher than its current utility U_x, the location is considered to be an option 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 r_{max} was set to full environmental view with negligible resettlement cost (see Section 3.3.1).

Apart from the aforementioned implemented actions, yet another "agent – environment action" that is not, however, under the direct control of the agent, is that of *hatching*, *i.e.*, generating offsprings. Hatching does have an impact on the agent utility (since this is affected by the overall population, via Equation 3.1), but the agent can only affect its probability of generating offspring by making sure that he is accumulating enough utility via the rest of his actions. This will become clear in Section 3.1.3 below.

Action: Hatching. A household agent may generate an offspring with some probability (*cf.* Section 3.1.3). When an agent generates an offspring, a newborn individual is added. If the new size of the household is higher than the defined maximum number of individuals per household, a new agent is created (agent offspring) by splitting the old household in two random sizes in the same environmental cell. If, by doing so, the maximum number of agents per cell is reached, the newly created household (agent) is located in any adjacent cell that has fewer agents than the maximum possible. The maximum number of agents per cell is derived by dividing the maximum number of individuals per cell with the maximum number of individuals per household. These parameters are user-defined and can be set using existing archaeological estimates.

3.1.3 Population dynamics

The total number of agents in the system changes over time, as individuals (inhabitants) belonging to households are born or die. The *death rate* [4] 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; 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:

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

[4]Certainly though, when agent's utility and storage reach to zero, an agent's individual inevitable "dies", thus, is removed by the system (and organization).

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

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

However, whenever $U_x < U_x^{thres}$, the agent attempts to "replenish" U_x by acquiring energy by its storage (or, when 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* (equals to 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 [30].[5]

3.1.4 Cultivation systems

Our ABM framework can 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 Bronze Age agricultural regimes [60, 77]:

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

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 $1,500$kg/ha, while the production associated with extensive agriculture is $1,000$kg/ha. These values are appropriate estimates for these two cultivation systems, given the period modeled [71]. Intuitively, the number of candidate cultivation cells (or fields) and the expected maximum energy stored for any agent in the model, depending on the agricultural regime in

[5]Others estimate growth rates in mainland Greece and the Aegean to be between 0.1% to 0.4% per year, for long periods during the Neolithic Era and the Bronze Age [2, 76].

use, is shown in Figure 3.4, assuming a grid (cell) resolution of one hectare (ha). An example of how these two different agricultural practices are actually used by the agents is the following: a household agent x with five individuals ($j = 5$), needs to accumulate $U_x^{thres} = 5 \times 250 = 1,250$kg of resources for the year, assuming $res_{min} = 250$kg (*cf.* Equation. 3.4). If agent x adopts an *intensive* agricultural strategy (producing $\mu_{max} = 1,500$ kg/ha), it chooses *one* (unoccupied) nearby cell ($1 \times 1,500 = 1,500$kg) from its settled location for cultivation, since that much is enough for sustaining its individuals for the current year ($U_x^{thres} < 1,500$). On the other hand, if agent x adopts an *extensive* agricultural strategy (assuming that produces $\mu_{max} = 1,000$kg/ha), it chooses *two* (unoccupied) nearby cells ($2 \times 1,000 = 2,000$kg) from its settled location for cultivation, since one cell (ha) is not enough for sustaining its individuals for the current year ($< U_x^{thres}$), thus expanding its farming land area.

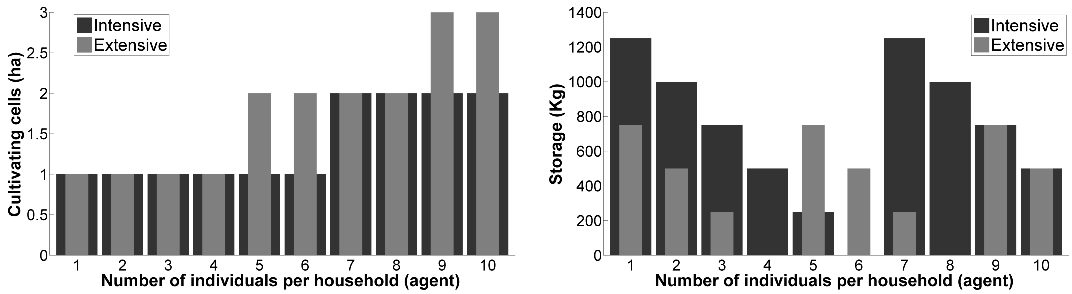


Figure 3.4: Number of cultivating cells (*left*) and maximum expected resources stored (*right*) for a household agent with respect to intensive and extensive agricultural practice.

3.1.5 Relation to existing models

Our ABM was originally inspired by the work of Janssen [74], and thus shares several basic features with that model. For example, 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 decision-making process. In particular, agents in [74] appear to be utility-based to some extent—even though the author does not use the term "utility" explicitly, and even though interactions in his model (like the sharing of resources among the agents, or the exchange of resources among their settlements) are to a large extent (if not entirely) pre-specified in the system. Apart from these similarities, the models are distinct to all other aspects.

To begin with, individual members of household agents introduced in that model are static, not affecting the agent or the ABM in any way. By contrast, individual household members are present and key in our model, since *(a)* their number affects the estimated agricultural production quantity (via Equation 3.1), and *(b)* for certain social organization models, they play a crucial role in determining how the accumulated resources are to be distributed among the agents (*cf.* the "egalitarian" organization model described in Section 3.2). Second, the modeling area in [74] 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 the agent 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 cultivation systems—our agents use either intensive or extensive farming, instead of cultivating just one cell.

Moreover, in [74] the production yield (harvest) is exactly the same for each agent within a settlement (cell), thus potentially violating maximum resource levels of the occupied cell. Production and thus agent utility is essentially affected by resource regeneration rates defined, and the agents make no attempt for actual utility maximization, apart from considering migration when resources at the current cell are exhausted. Indeed, the main agents action appears to be migration rather than cultivation, as the reported agent migrations number is proportional to population size, notwithstanding the fact that a settled farmers society is being actually modeled. 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 practice employed, or by migrating to another location or settlement for farming purposes, if such an option is deemed beneficial in terms of expected utility. In addition, in [74] the expected agricultural production is affected by estimated rainfall, 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.* Section 3.1.1) 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 [74]. 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 [74], and they are also instantiated on different modeling areas and time periods, thus this discrepancy might not be surprising.

3.2 Modeling Social Organization

Agents in our ABM have also actions by which they interact with each other. These *agent – agent actions* correspond to distinct social [6] organization paradigms, determining the way by which distribution of resources takes place among the population. In our work here, we examine five different social organization paradigms: *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. Specifically, our ABM can employ the following behavioural modes or resource distribution schemes:

Independent. Agents acquire (harvest) and consume resources independently. Although their 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 and the overall welfare of the settlement (*cf.* Equations 3.1 and 3.3).

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

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 household agents 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 with other agents. These relations determine the way resources are ultimately distributed among the agents. In the following sub-sections, we provide a detailed description of the internal process of this social organization paradigm.

Hierarchical (Static). 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. In our model's current implementation, the determination of the original relations, and the actual resource distribution takes place following the same rules as those governing the self-organized social organization paradigm (described in the subsections below).

Now, 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. For example, the emergence of palaces in the Middle Minoan (MM) 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 [19]. There is also a belief that stratification in Minoan Crete precedes the appearance of the palaces by several centuries [52, 14]. In our work here, we examine whether the adoption of a self-organized agent organization (settlement) will indeed give rise to a dynamically stratified social structure which will be able to sustain itself through time.

As mentioned in Section 2.2, the work of Kota in [81] on "self-organizing agent organizations" is an example of a recent *decentralized structural adaptation* mechanism originating in the multi-agent 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 Section 3.2.2 below. In effect, and in distinction to 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 in the subsections below.

3.2.1 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. We assume that 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 (task's resource amount). 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 for the area and era under study (specifically, in Greece before the Middle Bronze Age [62]). Thereafter, agents reorganize and *adapt* their relations, maintaining a dynamic stratified social structure. We elaborate 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 no relation exists among two agents, 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 process: *(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 he 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 reorganization (adaptation) process we describe below, both concerned agents will have to agree on changing their relation.

3.2.2 Task execution and allocation, and social re-organization

Mirroring the work of Kota [81, 82], our self-organization algorithm has two main stages: the *task execution and re-allocation* mechanism, by which agents deliberate on how they can allocate produce (energy resources) to other agents to cover their needs[7], based on their relations; and the *re-organization (decentralized structural adaptation)*

[7] We note that the notion of “lineages” for agent organization evolution has been implicitly introduced in the way 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.

one, used by the agents 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 agent x needs to execute a task, *i.e.*, when $U_x^{thres} - U_x > 0$, it will allocate the task (or subtask) to self if possible (*storage* > 0).

(ii) Otherwise, agent x will try to allocate the task to one of its *capable* superiors, 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 agent x nor its superiors are capable of executing the task, then x 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, agent x will try to allocate it to one of its *subordinates*, who must in turn find other superiors or peers to allocate the task to.

(v) On the occasions when agent x 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 resource exchanges among the agents, and these exchanges in turn lead to the formation of a dynamic "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*; this load intuitively represents the amount of resources expected to be returned in the future by the community. 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:

$$l_{x,tot} = \sum_{t \in T_x} res_t \tag{3.5}$$

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 resources 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 agent 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 agent 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 agent 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 agent 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 re-organization 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.*, $rmv\_auth_{y,x}$ $+form\_peer_{x,y}$. Composite actions are necessary as a pair of agents cannot have more than one relation (state) with each other. 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 V with the general form:

$$V(a, x, y) = \pm rdLoad(x, y) \pm L \tag{3.6}$$

where $rdLoad_{x,y}$ is the *relative difference* between the load on x and y; and L is 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 Figure 3.5.

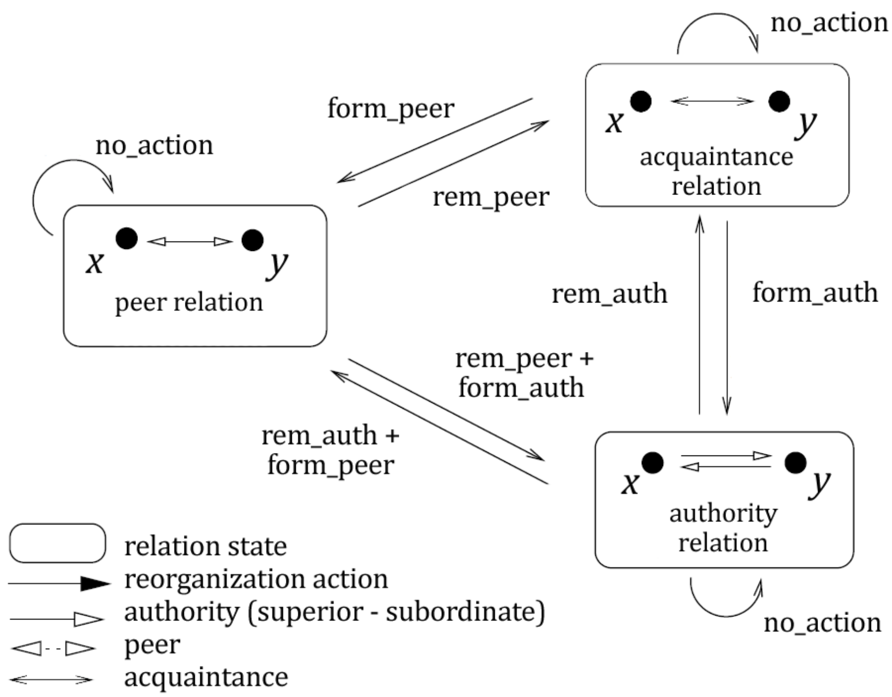


Figure 3.5: Relations state transition.

Table 3.1 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 to those used in the work of Kota [81].

Action	Action Evaluation Function Used
$a = form\_auth_{x,y}$	$V(a) = (l_{x,tot} - l_{y,tot}) / \max\{l_{x,tot}, l_{y,tot}\} - L$
$a = rmv\_auth_{x,y}$	$V(a) = -(l_{x,y} - l_{y,x}) / \max\{l_{x,y}, l_{y,x}\} + L$
$a = form\_peer_{x,y}$	$V(a) = -\lvert l_{x,tot} - l_{y,tot}\rvert / \max\{l_{x,tot}, l_{y,tot}\} + L$
$a = rmv\_peer_{x,y}$	$V(a) = \lvert l_{x,y} - l_{y,x}\rvert / \max\{l_{x,y}, l_{y,x}\} - L$
$a = no\_action$	$V(a) = 0$

Table 3.1: Atomic reorganization actions, and their action evaluation functions.

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 $V > 0$ 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 $< 60\%$—*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 for re-organization action $rmv\_auth_{x,y}$ allows an output value $V > 0$—*i.e.* $l_{x,y}$ is approximately equal to $l_{y,x}$ or $l_{y,x}$ is greater to $l_{x,y}$, and thus there is no reason to believe that agent x is superior to y. Finally, the agents may dissolve a peer relation (action $rmv\_peer_{x,y}$) when their relative current load difference is $> 60\%$, *i.e.*, $l_{x,y}$ is larger than $l_{y,x}$, allowing an output value $V > 0$. We need to note here that no_action has a default output value $V = 0$, thus, a positive output value $V > 0$ is necessary for an action to be executed.

Notice that the numerator of 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 agent x considers *dissolving* a relation with agent 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 V for any action; for instance, they would agree on the value of action $form\_auth_{x,y}$, *i.e.*, on the utility of agent x being superior to agent 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 agent 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 agent 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 3.1). 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 [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.[8]

3.2.3 Self-organization algorithm modifications

The *main* modifications[9] with respect to the self-organization algorithm in [81] 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 V. Our self-organization method aims to facilitate a targeted redistribution of wealth. Given this, V employs the notion of a *relative load difference* among agents (this is not done in [81, 82]). 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. In addition, agents in our model do not have "limited computational capacities", neither "communication costs". This is natural, since agents forge relations only with neighbours within their settlement organization.

3.3 A Case Study: Simulating the Minoan Society

In this section, we describe the employment of our ABM described above for the simulation of household agents, residing at the *Malia* area at the eastern part of the island of Crete, during the Bronze Age. The exact modeling area is depicted in Figure 3.6. It includes the *Malia-Sissi-Mochos* area, and also the *Lassithi Plateau* (near its center).

[8]We 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.

[9]There are other minor differences with the work of Kota [81, 82]. 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.

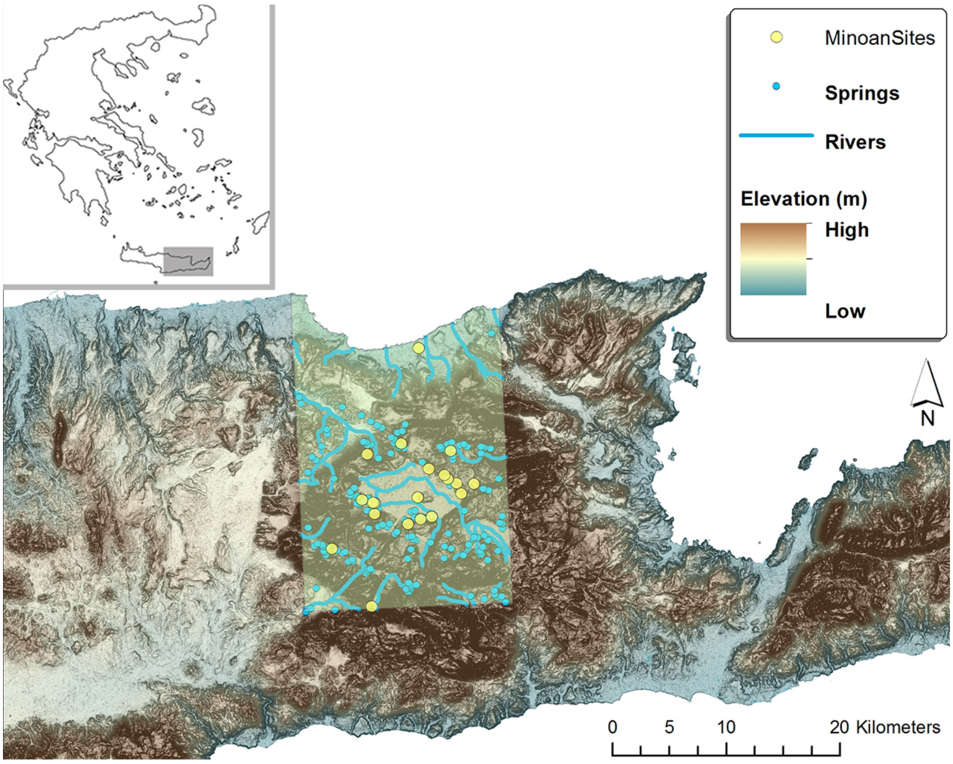


Figure 3.6: Modeling environment of the wider area of Malia, Sissi and the Lassithi Plateau, including known archaeological sites and aquifer locations.

As mentioned in Section 2.5, it is conceivable that interactions between different socio-political 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. Although any such specific hypothesis can of course be the subject of modeling, our main concern here is to keep our 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 2,000 years) spans essentially the entire Minoan period (*ca.* 3,100-1,100 BCE). Therefore, we are interested in exploring societal organization from the Early Minoan (EM) period, for which no clear evidence of social stratification exists [59], up to the Middle Minoan (MM) and Late Minoan (LM) periods, during which several localities on the island developed into centers of commerce and handwork, such as the Minoan Palaces.[10] Thus, at this stage, we try to explore the social organization in the micro-level of the artificial society, *i.e.* the organization evolution through interactions of "household" agents, about which little or no evidence can be obtained, rather than interactions between "settlement" agents in the macro-level.

Now, an ABM 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. Thus, one should always be very careful with parameter initialisation, so that these are based on archaeological 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 hypothesis. Given the above, and based on archaeological evidence on the Minoan society, our ABM simulation scenarios and results, that are able to sustain a high number of household agents and settlement sizes during the MM - LM period rather than the EM period, are also able to provide proper insights and suggestions on the social dynamics that might have occurred, during the area and era under study.

Nevertheless, the validation of the structural assumptions of the model itself is an easier (and almost straightforward) task. For example, we have already seen (*cf.* Figure 3.4) 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 case study.

[10] 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 [105, 61, 11].

3.3.1 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 initialized to a random number between 1 and 10. This choice originates to the fact that the estimated population per cell (ha) in an agricultural settlement during the modeled era was from 100 up to 300 [71]. The user-defined variable of maximum number of individuals per cell was set to 100; thus, the maximum number of agents per settlement's cell is 10,[11] *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 (*cf.* Section 3.1.4).

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 migration to another location (if during this period U_x is constantly less than U_x^{thres}). In our experiments here we use $yrs = 5$. The figure of 250kg was also used as the minimum amount of resources required per individual per year (res_{min}), based on [71]. The amount of resources is defined as the agricultural production R_i of an environmental cell i (*cf.* Equation 3.1); however, a cell's initial resources amount at a given run is multiplied with a sample from a standard normal distribution, and thus varies across runs.

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

Number of settlements per scenario: This parameter is user-defined. Its default value

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

was set, somewhat arbitrarily, to 2, since so many are known to exist in the archaeological record for the area in the beginning of the EM period.[12]

Agents migration radius: This is the distance agents can migrate to in one time step. It is also user-defined. In our simulation experiments here we set it to 25km (*i.e.*, the entire modeling area), roughly the distance covered when traveling on foot within a day [12]. Thus, the resettling cost rc for an agent was considered negligible—there is no requirement for extra time for rest, stops, overnight stays, *etc.*[13]

Agents agricultural practice: As mentioned in Section 3.1.4, intensive agriculture produces $1,500$kg/ha, while extensive farming leads to a production of $1,000$kg/ha [71].

Social organization paradigms: An agent can make 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: 60%).

3.4 Simulation Scenarios and Results

Various scenarios were taken into account for the experimental setup, with different parameterisation for: 5 different behavioural modes (*i.e.*, the social organization paradigms used); 2 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 [48]. 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 1,250m radius from the aquifer receiving a 100% initial production penalty. The exact penalty value for cells within the aforementioned radius, is provided by performing a *density analysis* of those locations, a spatial analysis tool that can calculate the density of input features (springs,

[12] Known archaeological sites information was provided by the GeoSat ReSeArch laboratory, available from the "Digital Crete" project.

[13] The resettling cost rc is defined and presented in Chapter 6, which was considered in the simulations.

rivers, sea/coastline) within a radius around each environmental cell. By calculating density, in a sense one spreads out the input values over a surface. The magnitude at each aquifer location is distributed throughout the modeled area, and a density value is calculated for each cell in the environment.[14] As already mentioned, at the beginning of each scenario resources are spread randomly over the land, but with resource amounts at a particular cell depending on its slope (as discussed in Section 3.1.1).

Each scenario was simulated for 30 runs, generating a total of 30×5 (behavioural modes) $\times 2$ (agricultural practices) $\times 2$ (settling near an aquifer requirement or not) $=$ 600 simulation runs. In addition, we experimented further with the "self-organization" social behaviour, testing 4 different values $(10\%, 40\%, 60\%$ and $90\%)$ of the ratio limit L for each cultivation system considered, and for 30 simulation runs each, under the assumption that residing next to an aquifer is a requirement. We run many more simulations for validation and sensitivity analysis purposes of the model that will be discussed later on. Simulation results were averaged for each time step. In terms of time, the process can be quite expensive, since a single run (composed of 2,000 yearly time steps) takes approximately 90 minutes on a single-core 2.6GHz computer. However, by employing additional computational power, the simulation process can be sped up significantly; we utilized the *Grid Computer* of TUC and by allocating a dedicated dual-core node of to a run, all 600 runs mentioned above were completed in less than a day.

All output data processing and statistical analysis tasks were performed with the Model Exploration Module (MEME) of MASS.[15] Results visualization (curve and bar diagrams or histograms) was done in MATLAB's (R2014b) 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

[14]Density value is computed using Kernel Density Estimation, based on the quartic kernel function [119].

[15]http://mass.aitia.ai/intro/meme

reproducible by any interested party. In addition, as a post-processing step for better visualization and reporting purposes, the Savitzky–Golay filter [115] was applied for smoothing only the curves of simulated data results.[16] The filter increases the precision of the data without distorting their tendency, by fitting successive sub-sets of adjacent data points with a low-degree polynomial with the method of linear least squares.

We now proceed to discuss our findings with respect to agents social organization behaviour and the agricultural schemes examined, and try to assess their impact on population sustainability, settlement numbers and sizes for the various scenarios in account.

3.4.1 Civilization sustainability

We begin with presenting our simulation results regarding the effect of the different social organization paradigms on the agent population as shown in Figure 3.7 for both agricultural practices. 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.

Simulation results of Figure 3.7 indicate that, during the end of the simulation (MM - LM period), population sizes in societies adopting the self-organization paradigm thrive, certainly under the intensive agricultural practice. 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 [52, 14].

Error bars corresponding to 95% confidence intervals regarding agent population

[16] We used MATLAB's *sgolayfilt* function with a 3^{rd} order polynomial and a frame length of 30 time steps for all simulation averaged data results.

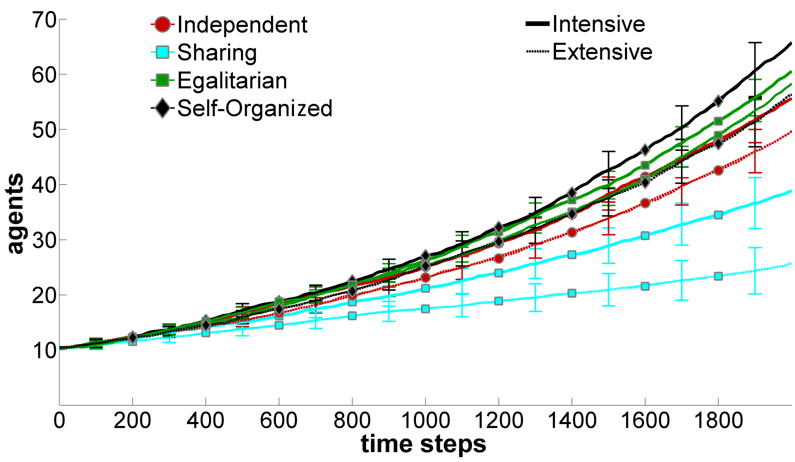


Figure 3.7: Agents population (number of households) over 2,000 yearly time steps, *wrt.* intensive and extensive agricultural practice, without a requirement for settling near an aquifer. Error bars indicate 95% confidence intervals.

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 Figure 3.7 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.

Figure 3.8a 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 Figure 3.8b.[17] 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 paradigm, the emerging development of many "small-size" settlements seems to be the way for survival over time. This fact is

[17]We do not show error bars for Figure 3.8 and Figures 3.9b and 3.9c (depicting settlements and agents/settlements). 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.

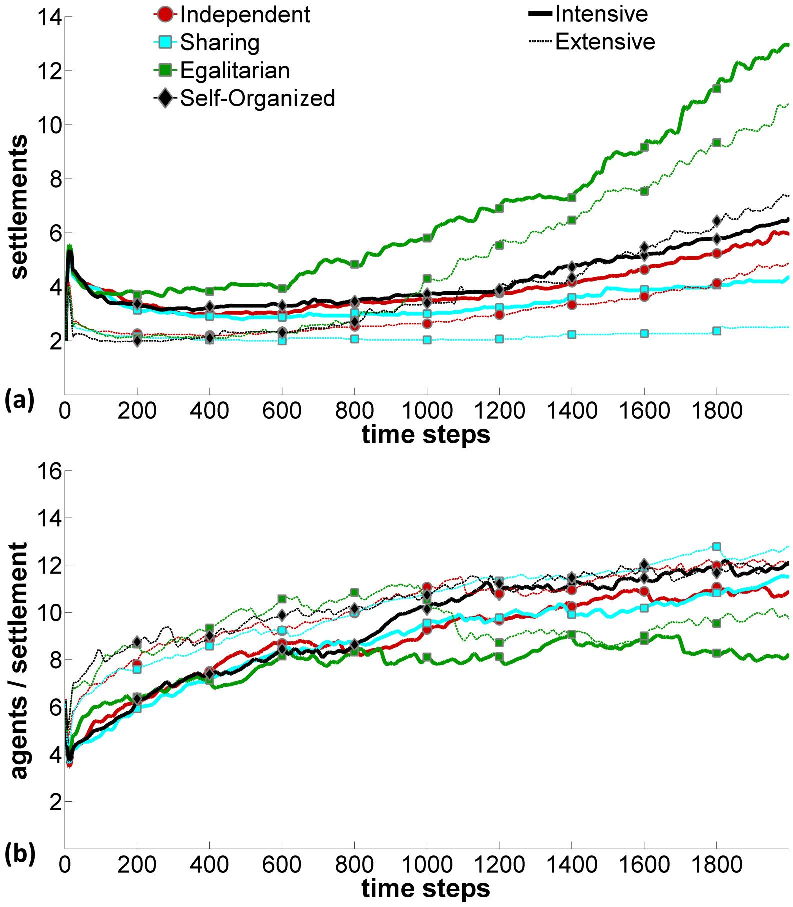


Figure 3.8: *(a)* Number of settlements and *(b)* agents per settlement—over 2,000 (yearly) time steps *wrt.* intensive and extensive agricultural practice, without a requirement for settling near an aquifer.

in contrast to archaeological evidence for larger settlements (towns and palaces) eventually coming to existence during the MM - LM period (*ca.* 2,000 - 1,100 BCE) [126].[18] Thus, though the simulation results of Figure 3.7 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 2,000 years, given its observed "requirement" for being developed primarily within small settlements.

[18]During the EM period (*ca.* 3,100 - 2,000 BCE), however, reviews of archaeological evidence for the Pre-palatial society visualize a "wholy undifferentiated" landscape, comprising very "small-scale autonomous local units" of a "small-scale intensive farming model", with no convincing evidence for "wealthy elites" [59]. This society later gave its place to the Minoan Palaces of the MM - LM periods.

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 follow the population growth estimated for that period (see Section 3.1.3). Indeed, this is confirmed in our results of Table 3.2, 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 $r = 0.1\%$. [19]

Aquifer requirement	*False*		*True*	
Agricultural practice	*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%)

Table 3.2: Individuals population size (and corresponding achieved percentage of estimated expected population size at the end of the modeled period) per social organization model, *wrt.* the cultivation system employed and the requirement for settling near an aquifer being false or true.

As a final note, the overall agent population is growing much larger when the *intensive* agricultural practice is used rather than the *extensive* one; this is expected, since resources harvested each year by agents utilizing extensive farming are generally lower in quantity (*cf.* Figure 3.4).

[19] The steady population growth rate r is achieved assuming agents are consuming adequate resources (*cf.* Section 3.1.3). In that case, the expected population size N after t (yearly) time steps is given by the equation $N = N_0 \cdot (1 + r)^t$ (where N_0 is the initial population).

3.4.2 The Importance of aquifers

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 [107]. In fact, archaeologists consider it very unlikely that human settlements in the Minoan times were established far from aquifers [3, 48]. 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.

Simulation results of Figure 3.9 are entirely similar to the results obtained in Figures 3.7 and 3.8, 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 Figure 3.9 confirm this intuition.

We also report our findings regarding the agent utility in this scenario (Figure 3.10a). Although it is slightly decreasing over time,[20] 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 Figure 3.9.

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 Figure 3.10b. Higher storage values that are seen when agents

[20]This is not unexpected, since, as the individuals' population increases, overexploitation leads to a slow production decrease (*cf.* Equation 3.1), and thus to a decay in utility.

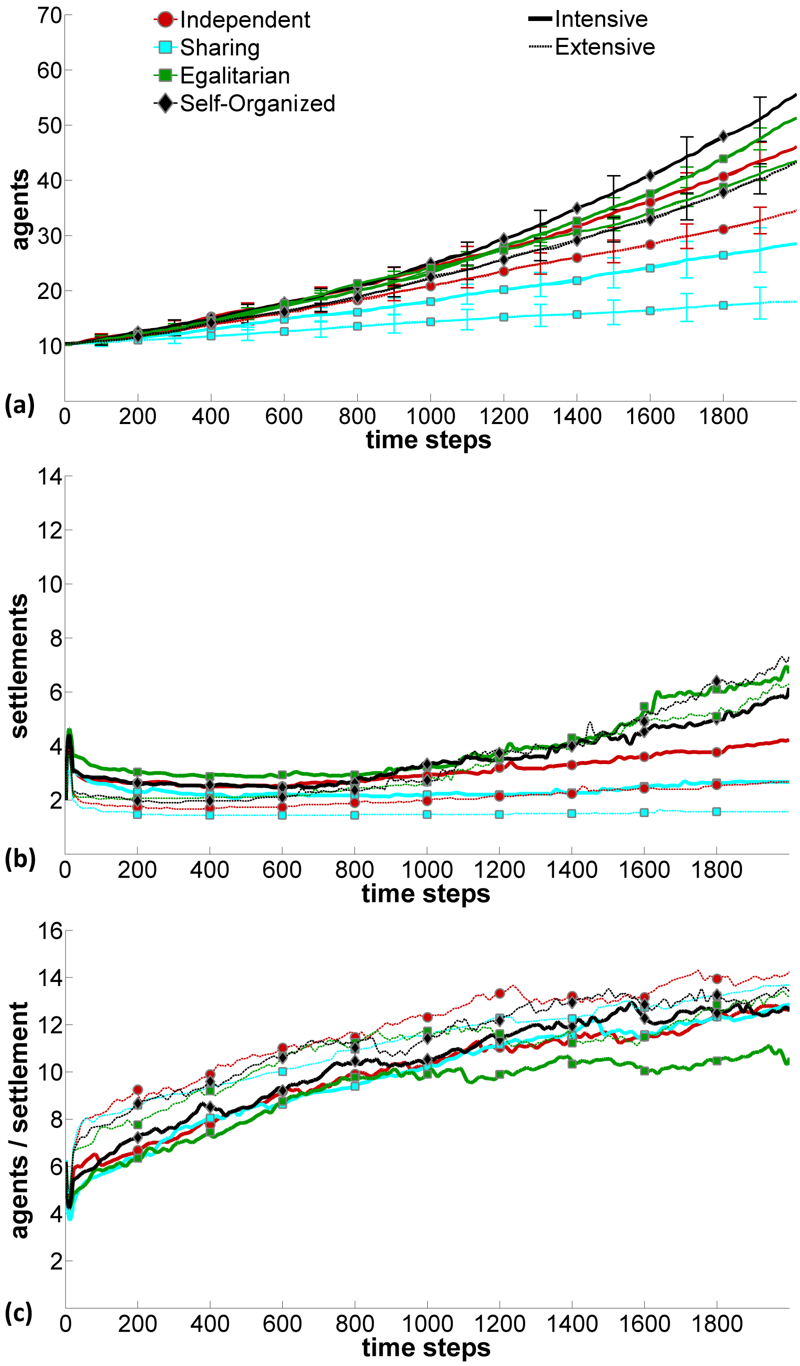


Figure 3.9: Number of *(a)* agents, *(b)* settlements, and *(c)* agents per settlement—over 2,000 (yearly) time steps *wrt.* intensive and extensive agricultural strategy with a requirement for settling near an aquifer. Error bars indicate 95% confidence intervals.

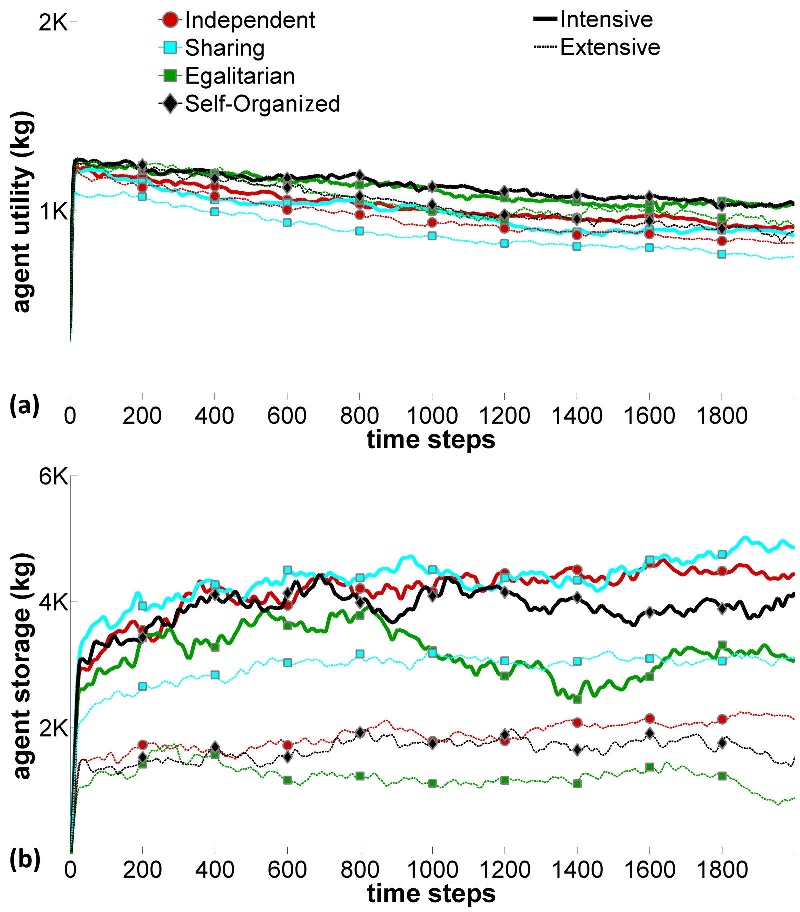


Figure 3.10: *(a)* Utility and *(b)* storage values of agents over 2,000 (yearly) time steps *wrt.* intensive and extensive agricultural strategy with a requirement for settling near an aquifer.

employ an "independent" social organization are due to their essentially "selfish", non-distributive behaviour. Even when the "sharing" social organization paradigm is in use, higher storage values observed are due to unexploited resources stored by "wealthier" agents exploiting their limited household sizes.

We close this section by noting that, regardless of aquifer proximity or agricultural strategy employed, settlements are concentrated near known (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 Figure 3.11. This is a phenomenon imposed by the modeling area's geomorphological characteristics (see Equation 3.1).

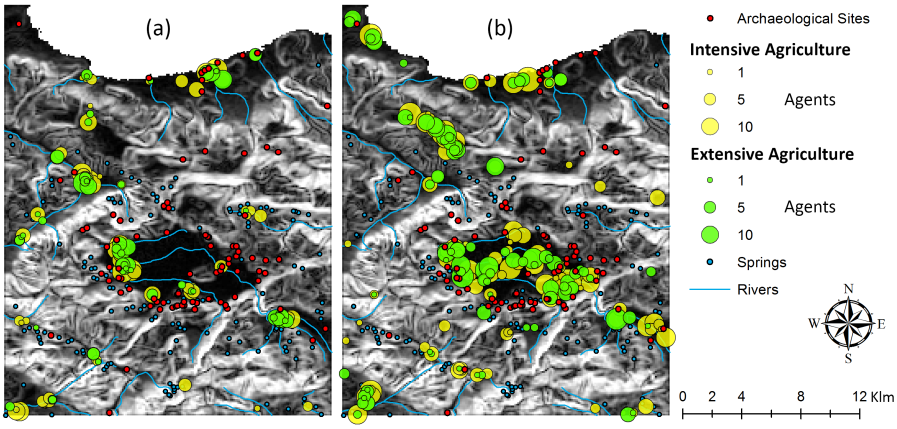


Figure 3.11: Settlement locations proportional to agent population size after 2,000 years; *(a)* with and *(b)* without a requirement for settling near an aquifer, employing a *self-organization* behaviour.

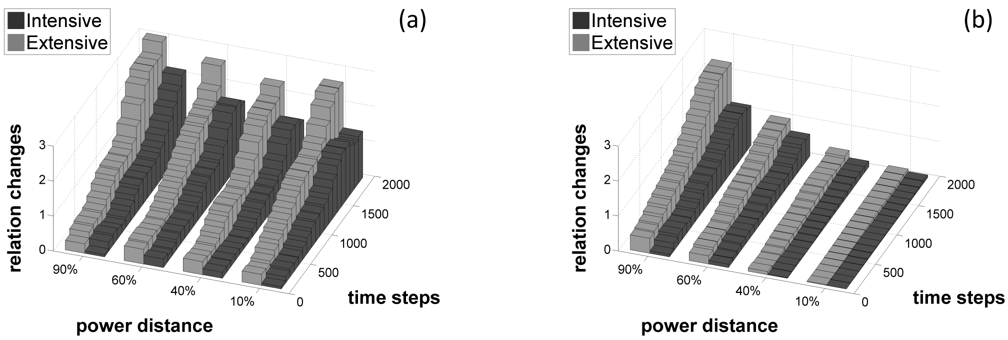
3.4.3 Self-organization: validation and insights

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 re-organization of the agents' relations on the other hand, based on their past and current experience on the 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.* Section 3.2.2 above). Therefore, in this section we will try to explore the agents organization's response to different degrees of power distance imposed upon the society.

Intuitively, we expect more peer relations to be formed among agents in the organization, as the power distance grows between superior and subordinate agents in an *authority* relation, 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 Figure 3.12b. When agents distribute produce with respect to their (type) relations, higher power distance rates seem to promote the development of additional peer relations among agents, expanding agents in the emerging hierarchy "horizontally", rather than "vertically" (as observed for lower power distance rates), a phenomenon that is intuitively correct.



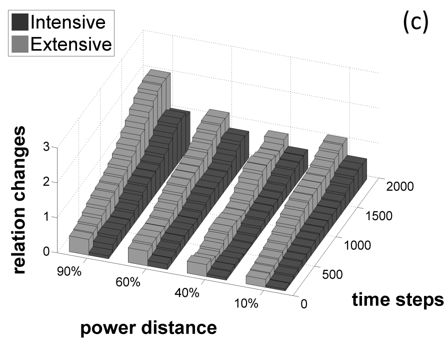


Figure 3.12: Average number of agent relation changes to *(a)* authority, *(b)* peer, and *(c)* acquaintance relation per century for various power distance rates *wrt.* intensive and extensive agricultural strategy.

The number of relation changes to an authority relation (Figure 3.12a) are at about equal level, regardless of variation in power distance. On the other hand, relation changes to an acquaintance relation (Figure 3.12c) 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 Figure 3.13.

Now, although the agents may "expand" their cultivation areas under the *extensive* agricultural strategy, they actually "gain" less energy amount harvested and stored (see Figure 3.4). 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 (*cf.* Figure 3.12).

Overall, the range of power distance in the artificial society, appears to have an impact on an the number of agents' relation changes, the type of relations the agents create, and the volume of resources agents exchange with others. We note, however, that there is a remarkably low average number of relation changes over time—*i.e.*, less than 3, as seen in Figure 3.12.

By contrast, the range of power distance seems to have a minor impact on the overall welfare of the agents. As seen in Figure 3.14a, agent utility remains almost invariable to lower or higher power distance among agent relations. Similarly, the produce stored by the agents (Figure 3.14a), as well as the agents population size, shown in Figure 3.14b, do not appear to be influenced by the underlying societal power distance.

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 simulations 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 (*cf.* Table 3.2. However, while the number of agent organizations (settlements) grows with an approximately equal rate for both the egalitarian and self-organized social organization paradigms, the

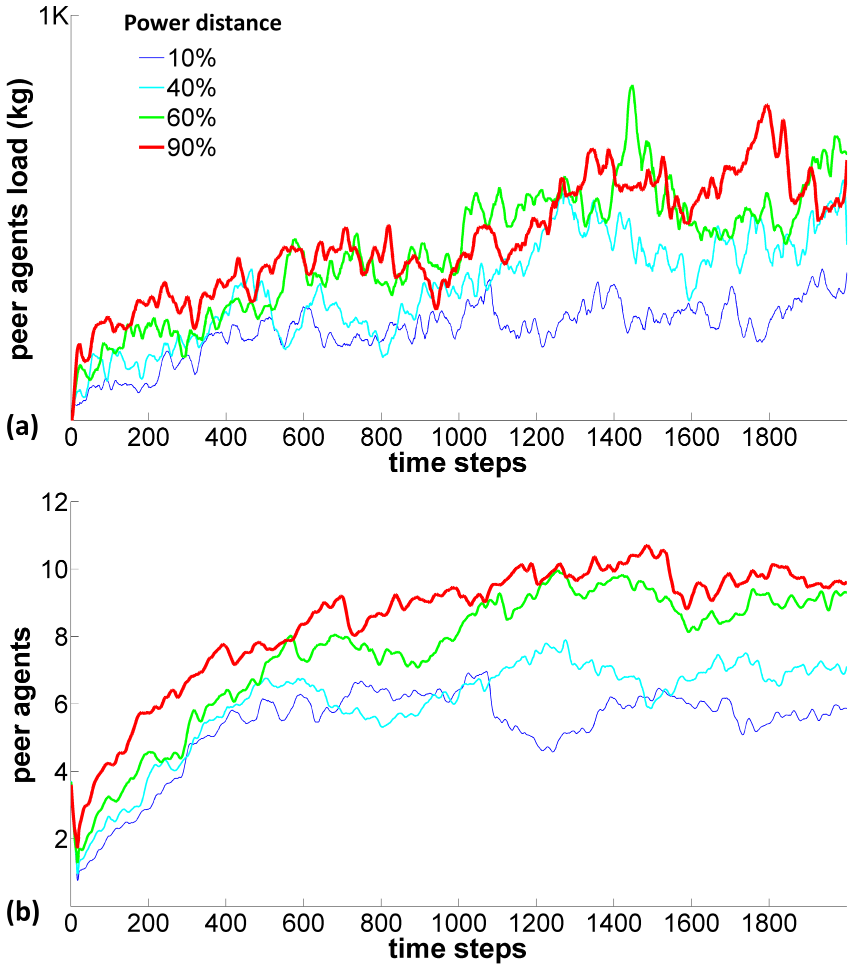


Figure 3.13: *(a)* Load and *(b)* number of peer agents for various power distance rates over 2,000 (yearly) time steps *wrt.* an extensive agricultural practice.

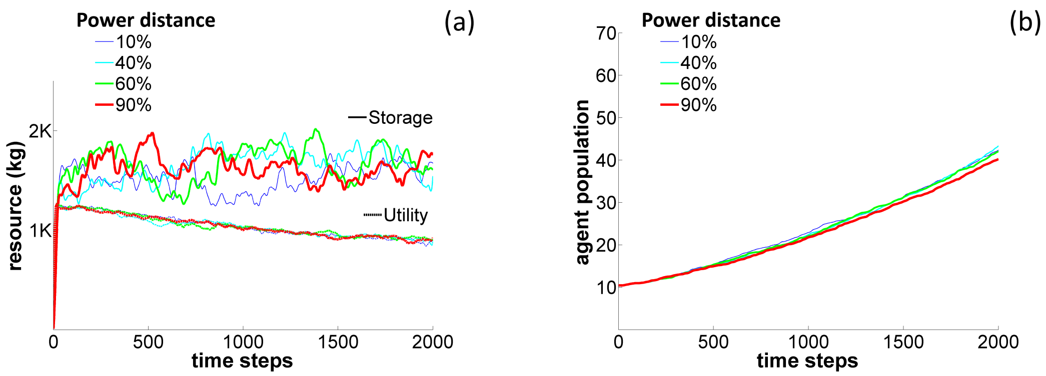
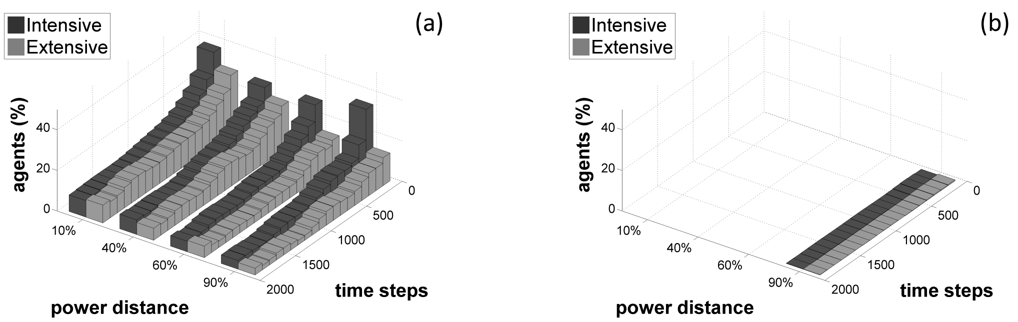


Figure 3.14: *(a)* Agents utility, storage and *(b)* population size for various power distance rates over 2,000 (yearly) time steps *wrt.* an extensive agricultural practice.

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 [107].

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 Figure 3.8 and Figure 3.9c), one could infer that a distributive social organization model which gave rise to a dynamic social hierarchy, such as the self-organized one studied here, is more probable to have existed for the 2,000 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 practices employed by the agents (*cf.* Figure 3.10b).



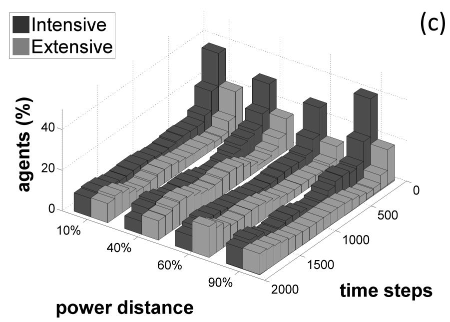


Figure 3.15: Percentage of agents with non-composite *(a)* superior, *(b)* peer, and *(c)* subordinate relation per century, for various power distance rates *wrt.* both cultivation systems.

Now, 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 Figure 3.15, 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 [32], *e.g.*, in our case, by the exchanged *load* among agents throughout the organization's 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 organization, domination and subordinate relations can be reversed, and privileges or status can be "redistributed" in each time step, following the needs of the organization.

3.4.4 Self-organization vs static hierarchical structures

As archaeologists assume a hierarchical social structure in later periods of the Cretan civilisation [19, 52], we now focus on a direct comparison of a social organization with "static" hierarchical relations among agents and a "heterarchical" social structure dynamically emerging through the underlying self-organization behaviour.

Agent and settlement population sizes are presented in Figure 3.16. 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 an intensive agricultural practice is used (Figure 3.16a). Settlement numbers are at about the same levels for both social organization paradigms (Figure 3.16(b)).

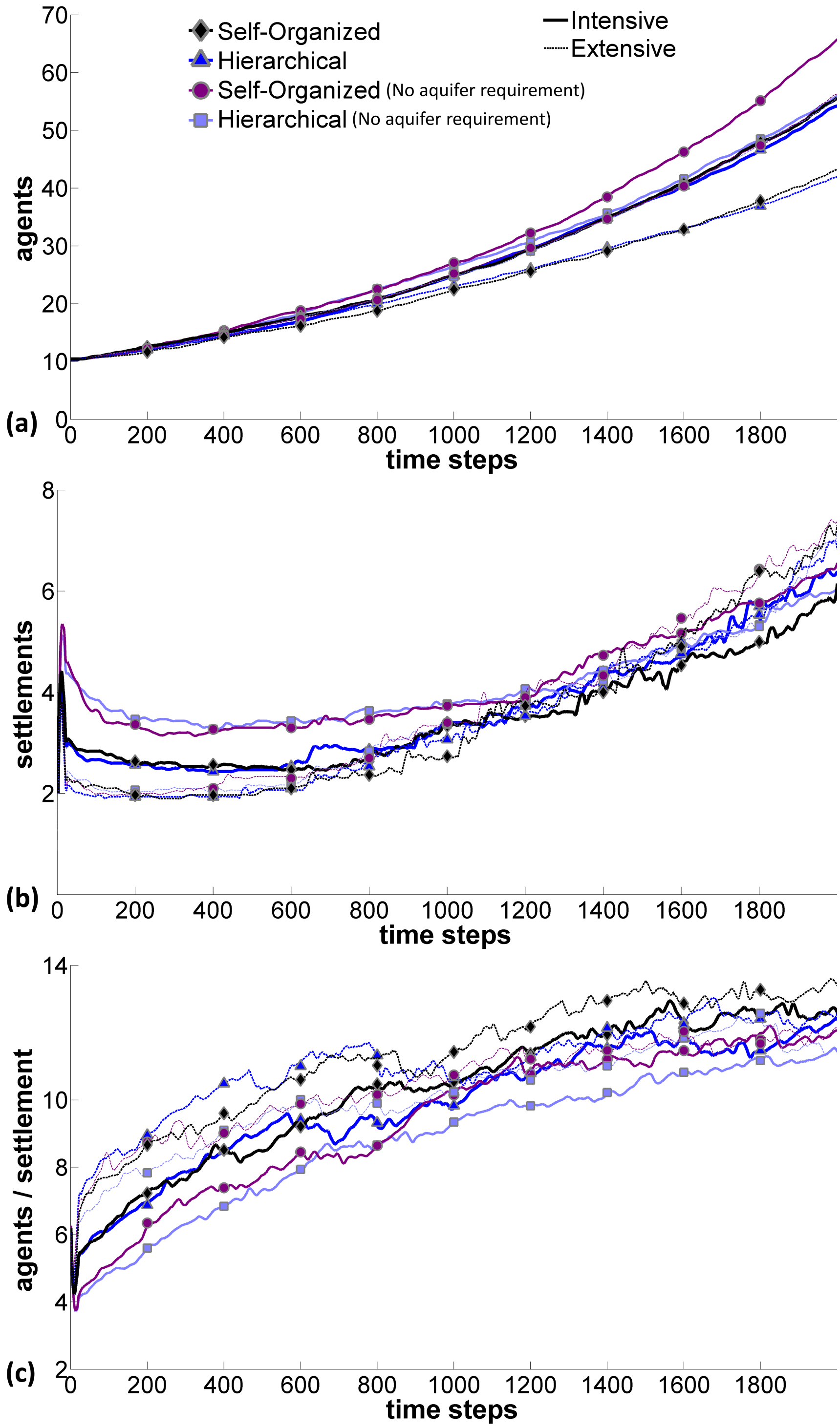


Figure 3.16: Number of household *(a)* agents, *(b)* settlements and *(c)* agents per settlement over 2,000 (yearly) time steps *wrt.* intensive and extensive agricultural strategy, and with settling near an aquifer being a requirement or not.

Moreover, in Figure 3.16c we observe that the self-organization social paradigm appears to have a slight advantage against the static hierarchical one, *wrt.* 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.* Figure 3.8b and Figure 3.9c). 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 Figure 3.17.

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 2,000 years period in question), especially for the geographic area modeled [117].

3.4.5 Agent migrations

Besides agent population numbers 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, 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 (Figure 3.18).

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 practice is used, agents migration activity can be considered trivial, since an agent considers migrating on average only once in a millennium. Thus, the migration ability modeled, appears to truly serve as the ultimate workaround for agents,

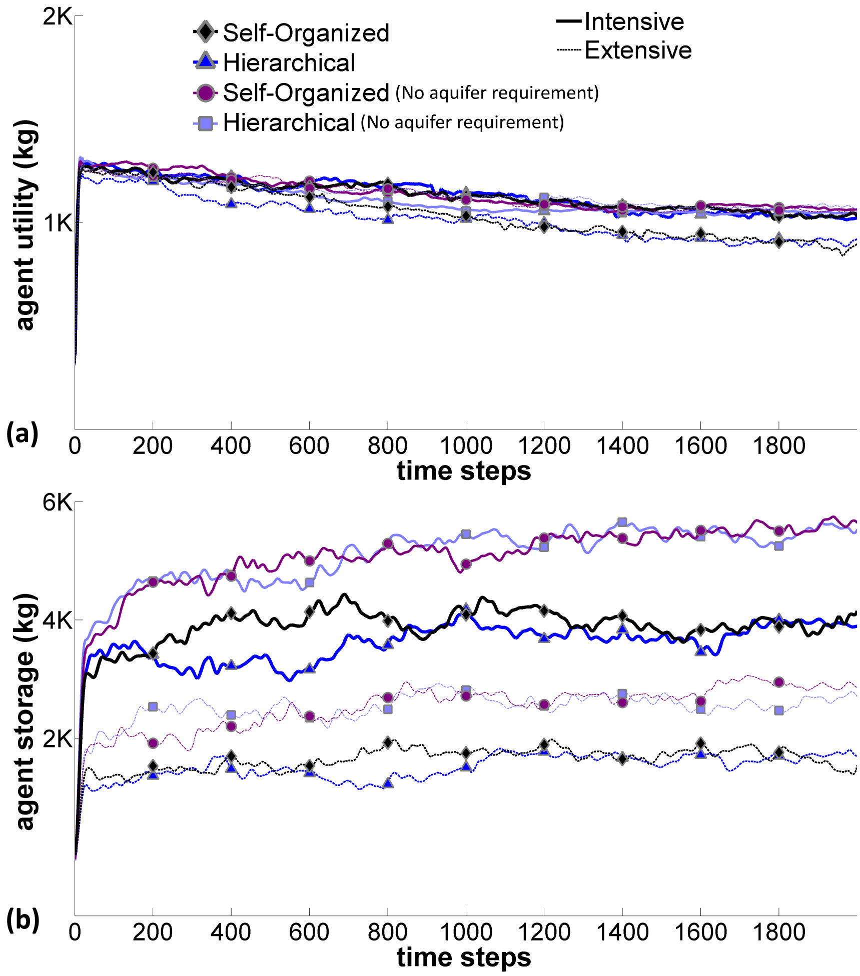


Figure 3.17: Agents *(a)* utility and *(b)* storage over 2,000 (yearly) time steps *wrt.* intensive and extensive agricultural strategy, and with settling near an aquifer being a requirement or not.

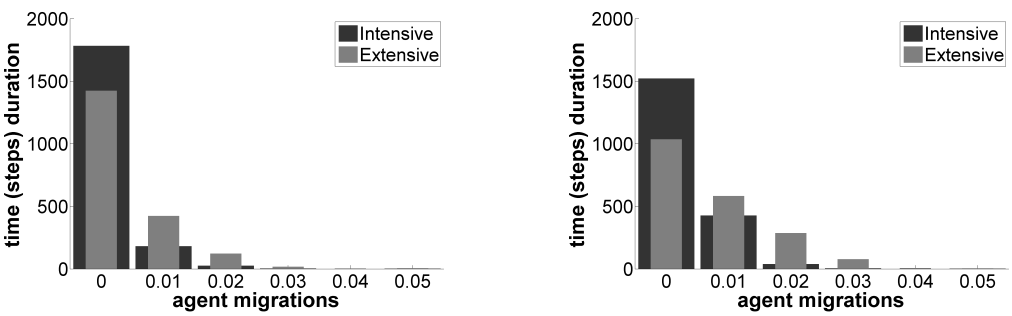


Figure 3.18: Histogram of number of agent migrations per time step for (*left*) egalitarian and (*right*) self-organized social organization paradigms *wrt.* both agricultural strategies.

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.

3.4.6 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) agent decision-making process, which uses a Markov Decision Process (MDP) [104] to decide on migration (or settlement) policies, and compare the viability (in terms of population growth over 2,000 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:

$$V(s)=\max_a\{\sum_{s'} P_a(s,s')(R_a(s,s')+V(s'))\} \tag{3.7}$$

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 Section 3.1.2), and $P_a(s, s')$ is the transition probability to s' when taking action a at s. The state value $V(s)$ essentially replaces an agent's x myopic estimate of Equation 3.3; thus, its utility at a given location s is now:

$$U_x = V(s) \tag{3.8}$$

In our implementation, the MDP solution determining the optimal $V(s)$ values and migration policies is provided by the well-known *value iteration* algorithm [104]. To keep things as tractable as possible, state transitions are assumed to be deterministic—*i.e.*, $P_a(s, s') = 1$. Further, we assume that the decision problem is only occurring (and, subsequently, an MDP needs to be solved) if the agent $storage = 0$, and his 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 a row (in our experiments in this subsection, we set $yrs = 10$). Once an MDP solution has been provided for an agent, the agent 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.

We have made several additional assumptions in order to ensure tractability while making the decision problem as realistic as possible. An agent's migration options are assumed to be restricted by both migration distance and terrain's 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" (see Figure 3.19). Thus, we assumed a finite horizon of 3 stages.

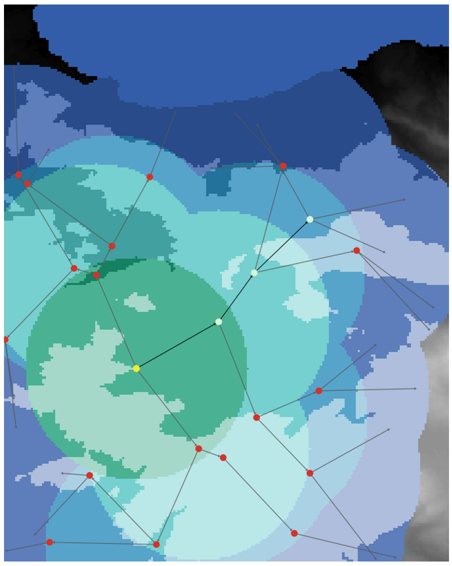


Figure 3.19: An example of states (red dots) and transition actions (grey lines) for an agent's MDP. States of the optimal policy are shown (white dots).

Moreover, we further classify the states according to environmental elevation as *low*, *medium*, and *high* elevation states, and we assume that agent movement is restricted given its current elevation state, as shown in Figure 3.20. For instance, if the current (state) location of the agent is at *low* elevation level, it can only transition to a *low* elevation state or to a *medium* elevation state (within its migration radius), 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 transition to m states per elevation level at each time step. In our experiments reported below, m was set to 1 for computational efficiency purposes.

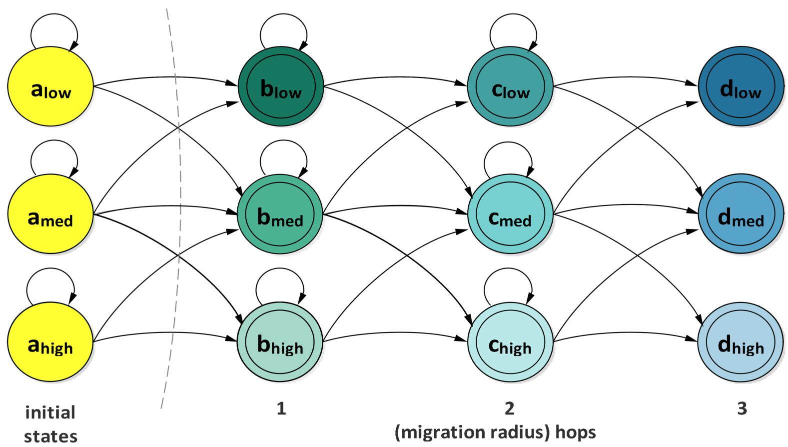


Figure 3.20: States (circles), collections of states (multiple circles) and transition actions (arrows) for an agent's MDP considering a 3-stage planning horizon.

Despite these restrictions, it takes up to 3 minutes to formulate an MDP and solve the decision problem of just a single agent at one time step, on a 2.6GHz single-core 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, that is, mainly determining the cells' immediate rewards, due to speed limitations of the programmable modeling environment.[21] Further problems arise from the fact that *(a)* multiple MDPs (corresponding to various agents planning problems) have to be dynamically built at any time step, since the rewards related to a given environmental step are not static, but fluctuate over time, as the result of the various agents settlement and cultivation actions (Figure 3.21); and *(b)* the fact that our ABM employs a fine resolution actual digital elevation model of the 50K cells modeling area. As a result, an entire 2,000 years simulation run takes on average 7 hours on a 2.6GHz single-core computer, when using the aforementioned parameter values.[22]

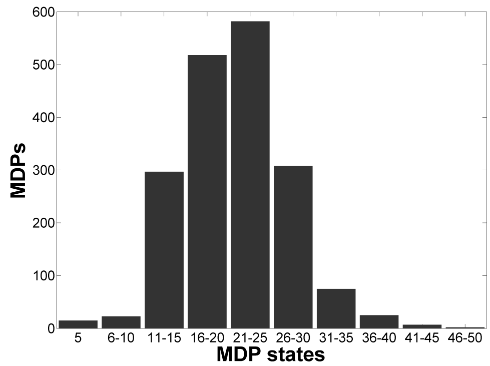


Figure 3.21: Numbers of dynamically created MDPs in an average simulation run, along with corresponding average numbers of their states, over 30 simulation runs.

Even with these restrictions in place, our simulation results confirm the intuition that an ability to "plan-ahead" is beneficial to the agents. Specifically, Figure 3.22 shows that, when compared to "myopic" agent decisions, societies of agents that use MDPs for planning migration policies achieve population numbers that are on average higher across the entire modeling period.

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

[22] 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.

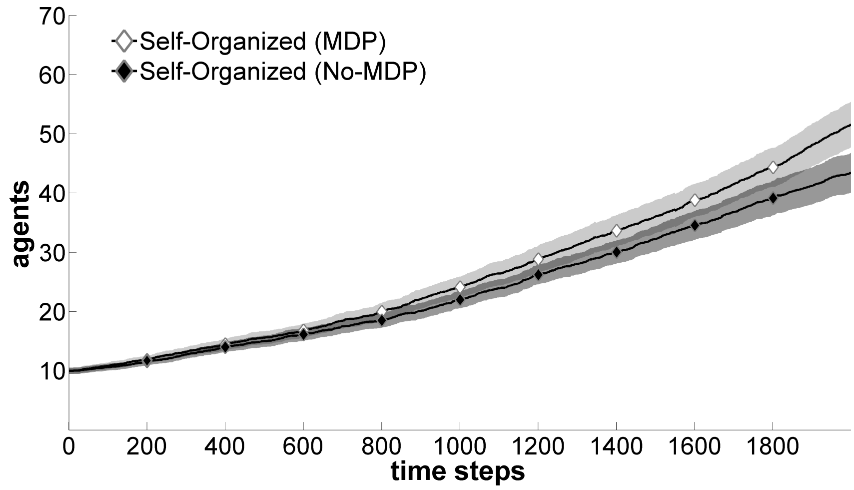


Figure 3.22: Number of household agents over 2,000 yearly time steps, using an intensive agricultural strategy, with a requirement for settling near an aquifer, using an MDP for decision-making or not. Error shading areas indicate 95% confidence intervals.

3.5 Conclusions

In this chapter, we attempted to showcase how to incorporate MAS-originating concepts and algorithms in archaeology-related ABMs. To that end, we designed and implemented a generic ABM system for archaeology research, adopting a utility-based agent architecture. Moreover, we incorporated into our ABM an appropriately modified *self-organization* method originally proposed for current agent organizations. Self-organization mechanisms have been observed in nature and biology and subsequently successfully applied in MAS research. Equipping ABM with such mechanisms can address problems that concern the emergence of system dynamics describing how the individual components interact with and respond to each other and their environment. However, such mechanisms had not been applied and tested in an archaeology simulations system before.

We employed our system in order to gain new insights into the social organization and agricultural activities of Minoan households residing at the wider area of Malia in Crete during the Bronze Age. Indeed, simulation results show that agent societies that adopt self-organization exhibit an increased viability over the entire 2,000 years of this period. Now, self-organization gives rise, naturally, to implicit agent hierarchies. As explained in Section 3.2, however, the wealthy are assumed to be helping out agents in need. Thus, our results here should by no means be interpreted as providing evidence for the sustainability of exploitative hierarchical societies. Rather, they could be interpreted as an indication that *targeted wealth redistribution* works better than a blind one.

Simulation results demonstrate that when agents adopt an “egalitarian” social organization paradigm, the emerging development of many “small-size” settlements seems to be the way for survival over time, while “self-organized” agent societies appear to be giving rise to larger settlements during their evolution. Moreover, 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 fact is in line with archaeological evidence for larger settlements (towns and palaces) eventually coming to existence during the MM - LM period, where a more varied and dynamic social structure is now suggested [41].

Chapter 4

An Evolutionary Game-theoretic Extension

As understood in the previous chapter, the various social organization paradigms explored assume a cooperative attitude on behalf of the agents. Specifically, agents were assumed to be willing to provide resources out of their stock in order to help agents in need, and such transfers drive the evolution of the social structure. In reality though, people are often driven by more individualistic instincts and exhibit more egotistic societal behaviour. Indeed, the evolution of civilisation and state appears to be driven by opposing, both competitive and cooperative, processes, which regulate behavioural relationships in a society [58, 118]. Therefore, if one is to model societal transformation accurately, agent behaviour has to be analysed from a strategic perspective as well. Assuming that agent interactions are based on rational decision-making, but are also influenced by their very effect on the society as a whole, then the evolution of the social dynamics can be studied via a game-theoretic approach [51]. It is anticipated that incorporating ideas from game theory and MAS research in ABMs can enhance agent sophistication, and contribute on the application of strategic principles for selecting among agent behaviours [135]. In this chapter, we adopt such an approach and provide an alternative agent self-organization social paradigm. Agent self-organization is driven by the interactions of *strategic* agents operating within a given social organization group, and the effects these interactions have on agent utility. As such, the evolution of the social hierarchies is driven by the interaction of agent strategies in an evolutionary game-theoretic (EGT) sense [122, 134]. This allows us to study the evolution and adaptation of strategic behaviours of agents operating in the artificial ancient community, and the effect these have on the society as a whole.

In more detail, we simulate repeated "stage games" played by pairs of agents, corresponding to "households" residing in Minoan settlements located at the wider area of Malia, in the island of Crete, same as in the case study of the previous chapter. Intuitively, the games model "resource exchanges" (utility transfers) among the households. The results of each game played contribute to the continuous alteration of the social structure, given the evolution of the differences in relative "wealth" among the agents. In contrast to most matrix games studied in the literature [103], our agents receive non-static *payoffs* (depending on their current utility, largely acquired via working the lands). Moreover, agent population is *not* constant, but fluctuates dynamically over time, due to utility-influenced births and deaths. Therefore, a strategy's reproductive success depends on dynamic payoffs, and thus agents using the same strategy do not necessarily receive the same payoff when interacting with others. This in effect lead us to an alternative model to the classic fitness-based evolution strategy selection: formulate the evolutionary dynamics based on evaluating agents', rather than strategies' *fitness*.

An agent employs a specific strategy when playing in the stage games and after a series of (yearly) time steps, agents assess and possibly modify their strategies (strategy review stage); strategy review and adoption is performed in various ways. Specifically, agent fitness can be evaluated with respect to solely the reward achieved in the games or the overall utility of the strategic agent (derived from game-playing and land cultivation), thus exploring the potential differentiation on the strategic behaviours adopted by the agents in the long-term. The relative success of the agent's current strategy (agent fitness) can be assessed at either the community (settlement) or the societal level, with respect to the average fitness of all strategic agents at that level, or the average fitness of agents adopting this particular strategy; while the adoption of an alternative strategy can be deterministic or stochastic.

We conduct a systematic evaluation of the performance of the various strategies and their adaptation methods. Our simulation results show that strategic agent populations are better sustained when agents base their strategy review decisions on the relative success of their current strategy with respect to the success of agents employing the same strategy; when the success of strategies is assessed at the community, rather than the entire societal level; and when strategy adoption is stochastic, rather than deterministic. Moreover, it is interesting to see that in the corresponding scenarios, agent populations converge to adopting cooperative strategies, despite this behaviour being in contrast to that prescribed by the stage game equilibrium.

Our work in this chapter provides several contributions, also illustrated in Figure 4.1 below:

- We extend our ABM framework that employs autonomous, utility-based agents, that are also able to self-organize, based on the interaction of agent strategic behaviours, in an evolutionary game-theoretic (EGT) sense.

- We blend for the first time evolutionary game theory with multi-agent systems' self-organization for modeling the evolution of strategic behaviours in a population of self-organized agents; specifically, we provide a novel evolutionary self-organization algorithm by simulating repeated "stage games" played by pairs of strategic agents, by means of which they exchange utility (corresponding to resources) with others.

- We provide an novel model for the evolutionary self-organization approach, where strategy review and adoption, agent fitness and the relative success of agents strategy are assessed and performed in various ways, which also differ considerably to those used in usual EGT approaches. This is because agents receive non-static payoffs and their population is not constant, in contrast to most matrix games studied in the literature.

- We conduct a systematic evaluation of the performance of various agent strategies, assuming several scenarios, for studying the evolution and adaptation of strategic behaviours of household agents operating in Minoan artificial communities, and the effect these have on the sustainability of the Minoan society as a whole.

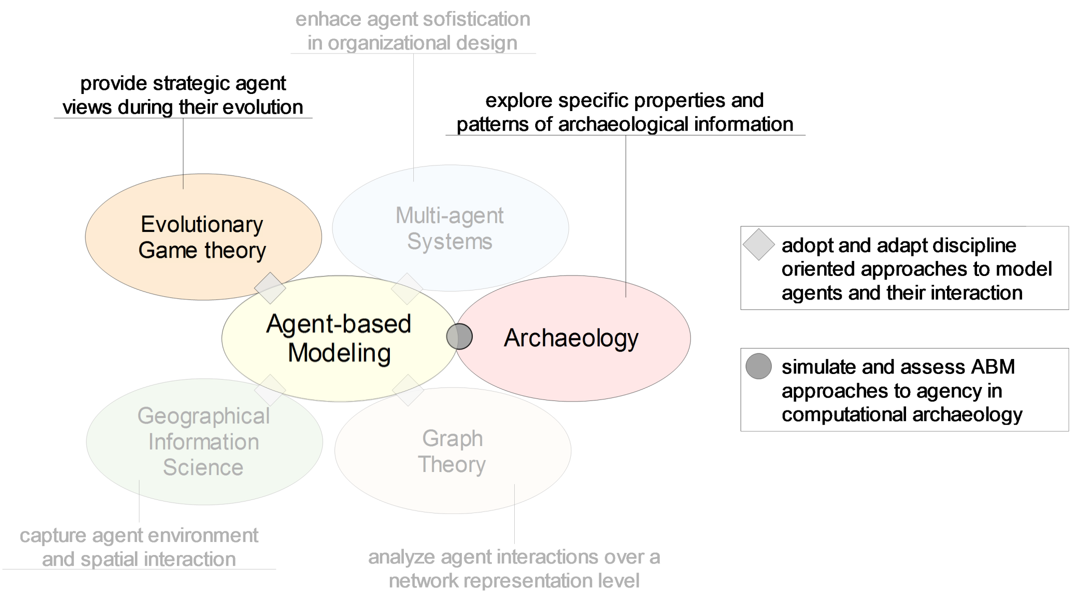


Figure 4.1: Overview of involved scientific fields and contributions in Chapter 4.

The remainder of this chapter is structured as follows. Section 4.1 provides a brief overview on the application of evolutionary game theory in social sciences, and in particular archaeology, as well as a summarized review of related examples in archaeological ABMs. Sections 4.2 and 4.3 present our ABM's evolutionary game-theoretic extension, coining an alternative self-organization framework: one that is driven by the interactions of *strategic* agents operating within a social organization group. Section 4.4 then records the empirical evaluation of our new approach—by first detailing the simulation parameters for the various scenarios considered, and then analysing the obtained results for our specific case study for an artificial society in a part of Minoan Crete. Finally, Section 4.5

concludes this work by providing main outcomes of our work presented here. Parts of the research described in this chapter appeared originally in [23], [24] and [25].

4.1 Related Work

There have been calls for the application of "evolutionary" concepts in the study of sociocultural phenomena, and the development of archaeological theories in that direction [44]. The "mathematics" of evolution are the subject of evolutionary game theory (EGT) [51, 134]. EGT originated as an application of the mathematical theory of games to biological contexts, arising from the realization that frequency-dependent fitness introduces a strategic aspect to evolution [94]. The interest among social scientists in a theory with explicit biological roots derives from the fact that the "evolution" treated by EGT is understood as *cultural* evolution, where this refers to changes in beliefs, behaviours and norms over time. Moreover, the rationality assumptions underlying EGT are, in many cases, more appropriate for the modeling of social systems than those assumptions underlying the traditional theory of games [94]. Thus, EGT imagines that the *game* is played over and over again by socially conditioned *players* (agents), each "preprogrammed" to some behaviour—formally a *strategy* in the game—and one assumes some evolutionary selection process operates over time on the population distribution of behaviours [134]. As such, EGT takes an interest in the *replicator dynamics* by which strategies evolve. Such dynamics typically assume that the share of the population using each strategy grows at a rate proportional to its current *payoff*, so that strategies providing the greatest utility against an aggregate previous period statistic grow most rapidly [51]. It is conceivable that taking evolutionary concepts into account in an archaeological theory in a principled manner, would require dealing with the "mathematics" of evolution.

The only archaeological related ABM that we are aware of implicitly adopting an evolutionary game-theoretic approach is that of [80]. The ABM is based on a mathematical model of a repeated "public goods game" put forward by [67], implementing a "birth-death" (Moran) process for studying selection dynamics in a *finite* population. The model simulates a voluntaristic process in which members of a society would prefer to live in hierarchically structured group, if "leaders" can reduce the likelihood of failures in cooperation due to free-riding or lack of coordination. The ABM in [80] adopts and adapt this game-theoretic model into an agent-based simulation, considering a simple reflex agent architecture, where "household" agents can exist in 3 states: thriving, just getting by, and perishing, depending on current resources stored. Agents reproduce according to a growth rate that provides for an approximately stable global population. Moreover, all *payoffs* (costs and benefits) from the game are *statically* expressed in resources (calories), representing punishment and tax payment costs, from and to the group "leader", for household agents that refuse or are unable to pay a full contribution, or for monitoring other group members to make sure that they contribute to the public good [80]. The authors examine the game-theoretic model's empirical plausibility by mapping it into a specific place and time, that is, in southwestern Colorado, known as the central Mesa Verde Region of the US Southwest, between about AD 600 and AD 1200. Simulation results of average number of strategic agents, groups and agents per group, from 36 different simulation scenarios (setup) are interpreted against archaeological evidence, suggesting that the early appearance of leadership in the modeling area could be explained by voluntaristic processes; however, the authors argue that larger group sizes and greater evidence for hierarchy observed, may require a model that explicitly incorporates inter-group competition.

Although there are numerous related works on "standard" EGT approaches applied on MAS and ABM, such as models to determine suitable "fairness" utility functions [33] or introducing behavioural diversity to study the co-evolution of a social network structure [128], we are not aware of any archaeological ABM that explicitly adopts an evolutionary game-theoretic approach.

4.2 Agent Strategies and the Resources Distribution Game

In this chapter, we explore an artificial society's evolutionary dynamics with respect to various *cooperative or not* agent behaviours. Thus, we need to introduce the ABM's main characteristics in terms of (evolutionary) game theory. Agents are considered as "players" in "stage games" that take place every time step corresponding to one year. In any such game, agents exchange (harvested) resources among them as follows. An agent's decisions regarding transferring resources to others correspond to its strategic "actions" in the games, and similarly, agent rewards (resource amounts transferred) are considered as "payoffs". Each game is between two agents, with agents belonging to the same settlement. At any given time step, however, a single player may be interacting at a one-on-one basis with many other agents within the settlement simultaneously. As such, multiple stage games are taking place simultaneously within each settlement. A player remembers its interaction history with every other agent, allowing this history to be taken into account by a player's (long-term) strategy. We assume a finite, but not fixed, population size, since new agents are created or old ones cease to exist.

In many domains, replication by way of simple biological reproduction is not a compelling parable for how behaviours spread in a population. In social sciences in general, replication by way of imitation and enforcement of *successful* behaviours is more appropriate [134]. In our work also, payoffs correspond to the decision makers' utility from interactions, and the replication mechanism is based on imitation and reinforcement of successful behaviours. In particular, each agent is "genetically" programmed to play originally some pure strategy k, and agent offsprings inherit the strategy the agent currently plays. An agent playing repeated stage games with opponents, sticks to some pure strategy for some time period consisting of *several* years, and then *reviews* its strategy, which sometimes results in a change of strategy. In our approach, we assume three simple player strategic behaviours: a *cooperative* one, C, willing to share resources with another player; a *defective* one, D, refusing to share resources; and one which starts with cooperation and then behaves as the other player did in the previous game round, namely *Tit-for-Tat*, TFT [5]. Considering these different strategic agent types as playing games against each other, we explore the evolutionary dynamics which arise. Agents payoff is interpreted as *fitness*, depending on the relative proportions of the different strategies in the population. Success in game playing improves utility, and is translated into reproductive success; strategic agents that do well over time reproduce more, while the ones that do poorly are outcompeted. This is straightforward natural selection [102]. As such, household agents' effective strategies continue to be used, and ineffective ones are dropped. We now describe the games setting in more detail.

The set of pure strategies K consists of $\{C, D, TFT\}$, and an agent that uses pure strategy $k \in K$ is a k-strategist. A TFT-strategist adopts C when playing for the first time, and in every further interaction adopts C if the opponent used C; and D if the opponent used D in the previous interaction. Therefore, agent actions can be condensed to C and D. Furthermore, we assume that a stage game takes place (among household agents in a settlement) as follows: any pair of agents contract to exchange a "share" of their utility. Suppose a pair of agents x and y exchange ε_x and ε_y respectively. Assuming that each fulfills their end of the deal, thus, "cooperating", then each receives a payoff calculated as the exchange received minus the one offered, e.g. $\varepsilon_y - \varepsilon_x$ for agent x. Suppose that agent y "defects" and does not deliver as promised, then the defector will receive the respective payoff of the opponent's exchange, ε_x, while the cooperator, agent x, will lose as much as the exchange offered, $-\varepsilon_x$. If both defect, then no one gains or loses anything. If we assume agent x and y payoffs as r_x and r_y respectively, the generic normal-form representation of a game between the agents is shown below in Table 4.1; the arrows imply that defection is the dominant strategy for any agent (agents have incentives to "move" towards defection), and mutual defection is the only strong Nash equilibrium. Note, however, that each stage game is one with "dynamic" payoffs (since rewards depend on the current agents utility).

Considering that there are ν players in a settlement, an agent interacts pairwise with all other $\nu - 1$ agents in the settlement. An agent is assumed to be willing to offer to

Table 4.1: Equilibria of the distribution game

		Player y	
		C	D
Player x	C	$r_y = \varepsilon_x - \varepsilon_y$, $r_x = \varepsilon_y - \varepsilon_x$	$r_y = \varepsilon_x$, $r_x = -\varepsilon_x$
	D	$r_y = -\varepsilon_y$, $r_x = \varepsilon_y$	$r_y = 0$, $r_x = 0$

opponents a portion of its total payoff, depending on the number of its individuals, κ, that "live" in the household. Thus, the exchange ε_x offered from a household agent x, is a function of the agent's current utility U_x and κ, and has the following form:

$$\varepsilon_x = \frac{U_x}{(\nu - 1)(\kappa + 1)} \tag{4.1}$$

For example, a household agent with 5 individuals, is willing to contribute to its $\nu - 1$ "opponents", $U_x/6$ of its utility, offering to each of its opponents $(U_x/6)/(\nu - 1)$ reward during a game interaction. Note that Equation 4.1 depends on agent utility U_x, which depends on resources harvested, and not just on resources received through games. At the end of each year, agents update their utility and reorganize their relations, based on their accumulated rewards via the games. The *total payoff* $r_t(x)$ from games for a k-strategist x at time t is:

$$r_t(x) = \sum_{\forall y \in O} r_x(i, j) \tag{4.2}$$

where O is the set of x's opponents at t and i, j are the actions prescribed by x's and y's strategies during an interaction. The *updated* utility $\tilde{U}_x$, of an agent x is calculated as:

$$\tilde{U}_x = U_x + r_t(x) \tag{4.3}$$

Note that for a D-strategic agent x, it is $\tilde{U}_x \geq U_x$ always, as such a player is unwilling to make any exchange, but may receive some reward from a cooperative contracted agent.

4.3 Replicator Dynamics

Now, the classic evolutionary model of *replicator dynamics*, assumes that a homogeneous population playing a particular strategy grows in proportion to how well that strategy is doing relative to the mean strategy population performance [51]. Since the agent population in our ABM is not constant, but fluctuates depending on agent utility, and since agents do not "identify" with strategies (but may adopt other strategies over time), we formulate the evolutionary dynamics based on evaluating *agents*', rather than strategies' fitness. Therefore, at any given time step t, the current *fitness* $f_t(x)$ of an agent x , is calculated as:

$$f_t(x) = \tilde{U}_x \tag{4.4}$$

Although we believe it is more natural for an agent to evaluate its fitness based on its utility, since population growth is utility-dependent in our ABM, in order to be in line with classic EGT approaches, in some simulation scenarios we also considered agent fitness to be based solely on its total reward from games it participated in. In those scenarios, agent x calculates its fitness at time t as:

$$f_t(x) = r_t(x) \tag{4.5}$$

At the end of some time period T, during which the agent plays games using strategy k, agent x evaluates its current fitness with respect to the average fitness of the organization, before (possibly) switching to any other strategy. The *average fitness* F of the organization over the period T, is calculated as:

$$F = \frac{1}{n} \sum_{\forall x \in S, \forall t \in T} \frac{f_t(x)}{|T|} \tag{4.6}$$

where $S = \{x_1, x_2, ...x_n\}$ is the set of all household agents in the organization, considering each agent's lifetime during period T. The term "organization" may actually refer to either the settlement in which x belongs, or the entire society of agents (across all settlements). Although agents always play games only with other agents in their settlement, in some simulation scenarios the set S in Equation 4.6 above refers to the entire society. This attempts to capture the fact that the views of the entire society regarding the value of the various behaviours (strategies), could weigh on an agent 's deliberations regarding the adoption of a specific "attitude" towards others. Moreover, assuming that agent x reviewing its strategy is currently a k-strategist, in some simulation scenarios we also calculate F with respect to the set S_k of k-strategists in the organization (settlement or society). That is, in Equation 4.6, we replace S (the set of agents in the organization) with S_k (the set of agents in the organization that share x's strategy). This attempts to evaluate how well x is doing with respect to agents exhibiting the same "attitude" towards others.

Agent x will consider switching to some other strategy, only if $f_t(x)-F < 0$, *i.e.*, its fitness is less than the average fitness of the organization under examination (settlement or entire society) during the previous period T. If that condition holds, x can choose to *deterministically* switch to some other pure strategy l with $max\{F_l\},\ l \in K$, where F_l is the average fitness of the l-strategic agents in the organization; or it can *stochastically* switch to strategy l with probability p_{kl} $(k, l \in K)$, based on the percentage of l-strategic agents (or l-strategists) in the organization, calculated as follows:

$$p_{kl}(x) = \frac{|S_l|}{n} \tag{4.7}$$

Note that, in that case, p_{kk} is considered to be the probability that a reviewing k-strategist does not change strategy.

Regardless of the strategy review scenario used, self-organization is now driven by the interactions of *strategic* agents operating within a given social organization group. However, the re-organization (decentralized structural adaptation) stage, used for re-evaluating and potentially altering agent relations, is the same as described in the previous chapter (*cf.* Section 3.2).

4.4 Simulation Scenarios and Results

In this section, we describe the employment of our extended ABM presented above for the simulation of the evolution of "household" agent societies, considering the same modeling environment as in the simulation scenarios of the previous section, *i.e.*, the wider area of *Malia* region at the island of Crete during the Minoan period. Model parameters were initialized to values set so that they correspond to estimates found in archaeological studies relevant to the period of study. The ABM's initial settings are the same as in the simulations in the previous chapter for evaluation purposes; specifically, strategic agents are assumed to cultivate the landscape by employing an "intensive" agricultural practice, with a requirement for settling near an aquifer location.

We conduct a systematic evaluation on the impact of the evolutionary self-organization social paradigm to population viability. Specifically, agents play games and *(i)* never review their strategy (*cf.* Sec. 4.4.1); *(ii)* review their strategy and perhaps deterministically switch to another (*cf.* Sec. 4.4.2); or *(iii)* review their strategy and perhaps stochastically switch to another (*cf.* Sec. 4.4.3). Furthermore, we consider strategy review *time periods* of either $T = 8$ or $T = 16$ years. Each scenario was simulated for thirty (30) runs, for a total of 990 simulation runs =30 (no review) $+$ 30 $\times$ 2 (strategy review options) $\times$ 2 (fitness function evaluated *wrt.* U or r_t) $\times$ 2 (time periods $T = 8$ or $T = 16$) $\times$ 2 (organization considered at the settlement or the societal level) $\times$ 2 (agents considered in the organization, all or only "same"-strategists). In terms of time, the process can be quite expensive, since a single run (composed of 2,000 time steps) takes approximately 40min on a single core 2,6GHz computer; by employing, however, additional computational power, *i.e.*, via allocating a dedicated dual-core node of TUC *Grid computer* to a run, all 990 runs mentioned above were completed in less than a day. Results visualization was done in MATLAB (R2014b) environment. In all figures, results are *averages over 30 simulation runs* across a period of $2,000$ years. Moreover, one may reproduce our simulation results via using the same random "seeds" that we used for the random number generators introduced in parts of our model.

In our simulations, we compare the performance (in terms of population growth achieved) of strategic agents that play games and use self-organization, which we term "SO evolutionary" agents, against those that *(i)* are benevolent and self-organize, simply termed "SO" agents; or *(ii)* adopt the "independent" social behaviour, trying to maximize their utility without interacting with others (*cf.* 3.2). Moreover, we report on the fraction of the population that adopts a cooperative attitude at each scenario. In order to not to clutter our results' figures below, we will depict shaded areas that correspond to 95% confidence intervals around lines corresponding to agent populations adopting an evolutionary approach (the "SO evolutionary" D-, C-, and TFT-strategic agents), and their aggregate line (marked "SO evolutionary"), and not for the SO or "independent" agents. Moreover, in order to assist the reader, in all figures the legends are ranked in accordance to the relative performance of their corresponding behavioural methods.

4.4.1 No strategy review

In our first scenario, there is no strategy review for the "SO evolutionary" agents. Results of this scenario are shown in Figure 4.2. We can observe that as time passes agent popu-

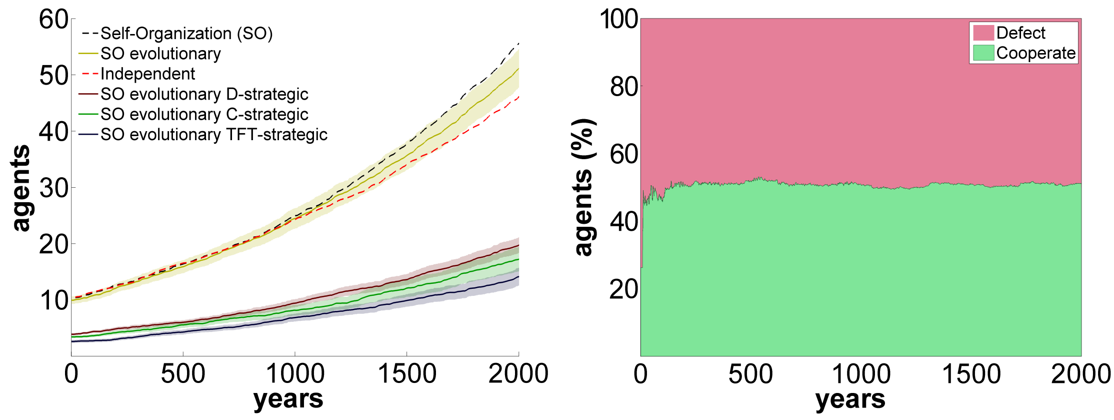


Figure 4.2: (*a*) Agent population, and (*b*) percentage of agent behaviours, for the *no strategy review* scenario.

lation increases, with a rate that ranges between those of the extremes in the model—*i.e.*, benevolent "SO" agents that always help each other, and "independent" (Figure 4.2a), while their social behaviour remains proportionally stable, i.e. $\approx 50\%$ of the agents cooperate or defect (Figure 4.2b). Note that, in that figure the percentage of cooperative or defective behaviour depicted, includes the current C or D actions of the TFT-strategists (since they adopt C or D depending on their past opponent action). Moreover, we report that TFT-strategists actually exhibit $\approx 60\%$ *cooperative* behaviour here.

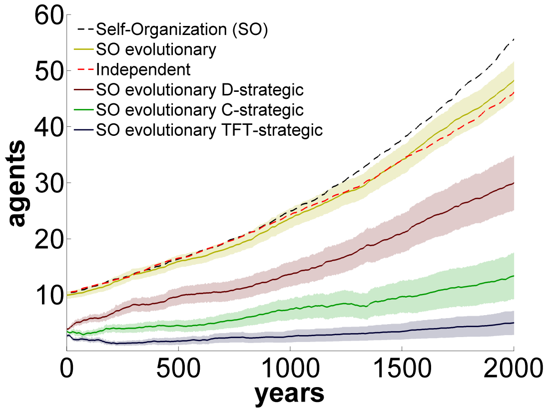
Let us now discuss our findings for the rest of the scenarios in turn. In all the following corresponding scenarios (sub) figures, we adopt the following notation: $F \sim U$, where agents fitness function is calculated by their updated utility (Equation 4.4); $F \sim R$, where agents fitness function is calculated by their total accumulated reward (Equation 4.5); $T = 8$ and $T = 16$ for strategy review periods of 8 or 16 years respectively.

4.4.2 Deterministic strategy review

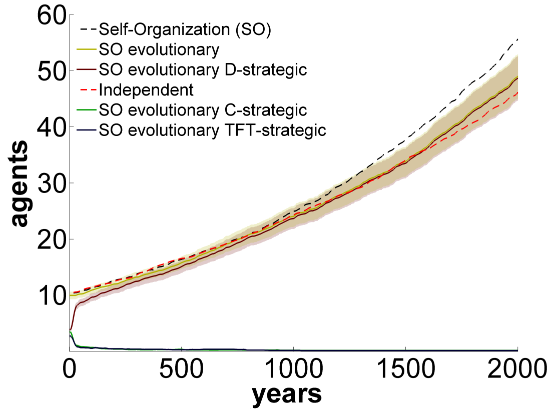
In this section we simulate agents which review their strategy k and, *deterministically* switch to strategy l with $max\{F_l\},\ l \in K$, where F_l is the average fitness of the l-strategic agents in the organization, where the organization is either the agents settlement to or the entire society.

Strategy review wrt. settlement performance

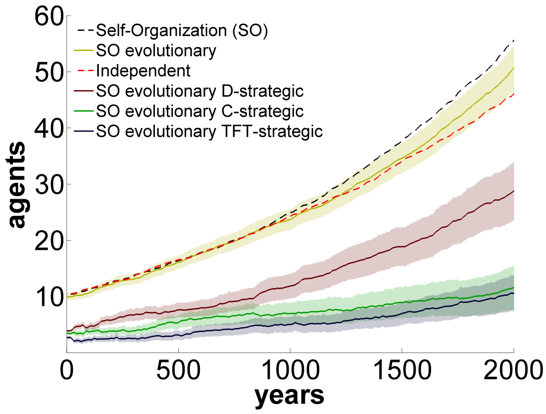
Here, the average total fitness (Equation 4.6) is calculated with respect to all household agents within the settlement (S in Equation 4.6 is the set of all agents in the settlement). Simulation results are shown in Figure 4.3. We observe an overall decline of the average population of "SO evolutionary" agents, with respect to the scenario of Figure 4.2, for most of the scenarios in this category (except for the scenario of Figure 4.3c). Moreover, the average number of D-strategic agents increases significantly, irrespective of agent's strategy review time period and fitness function.



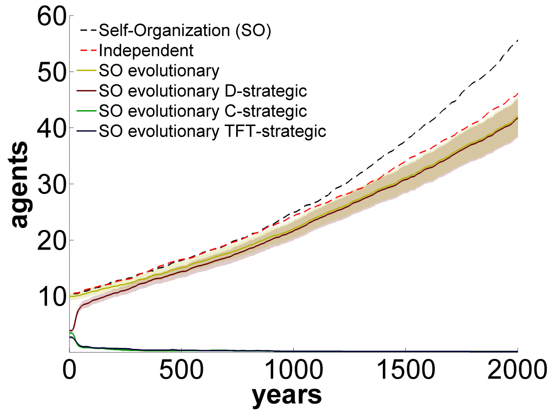
(a) $F \sim U, T = 8$



(b) $F \sim R, T = 8$



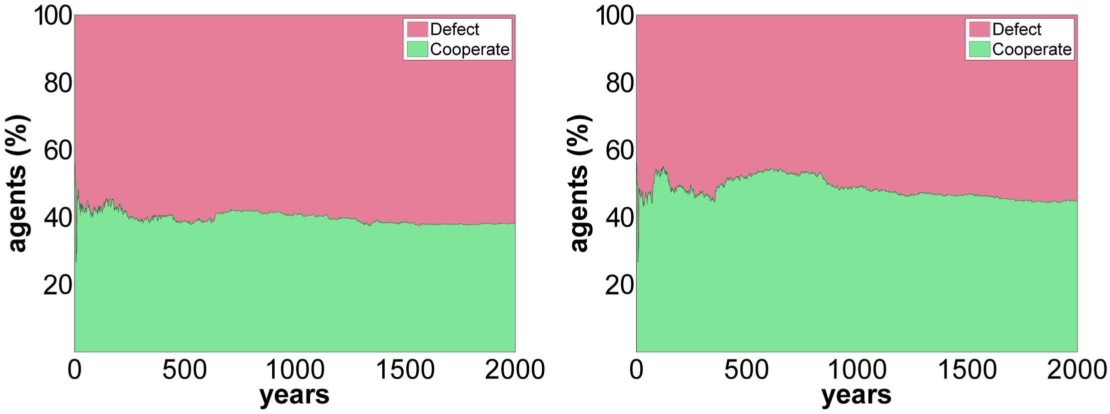
(c) $F \sim U, T = 16$



(d) $F \sim R, T = 16$

Figure 4.3: Agent population for scenarios with *deterministic* strategy review and F calculated across *all* agents in the *settlement*.

Results for the two scenarios where $F \sim R$ (Figures 4.3b and 4.3d), are as anticipated by the game equilibrium (Table 4.1). When $F \sim U$ (Figures 4.3a and 4.3c), we observe that cooperative behaviour is not completely extinct. However, agents adopt, on average, a defective behaviour; $\approx 60\%$ of the agents defect, irrespective of T values, as shown in Figure 4.4. In general, all scenarios in this category exhibit an overall defective behaviour with low average number of agents, similar to the "independent" behaviour mean population size.



(a) $F \sim U, T = 8$

(b) $F \sim U, T = 16$

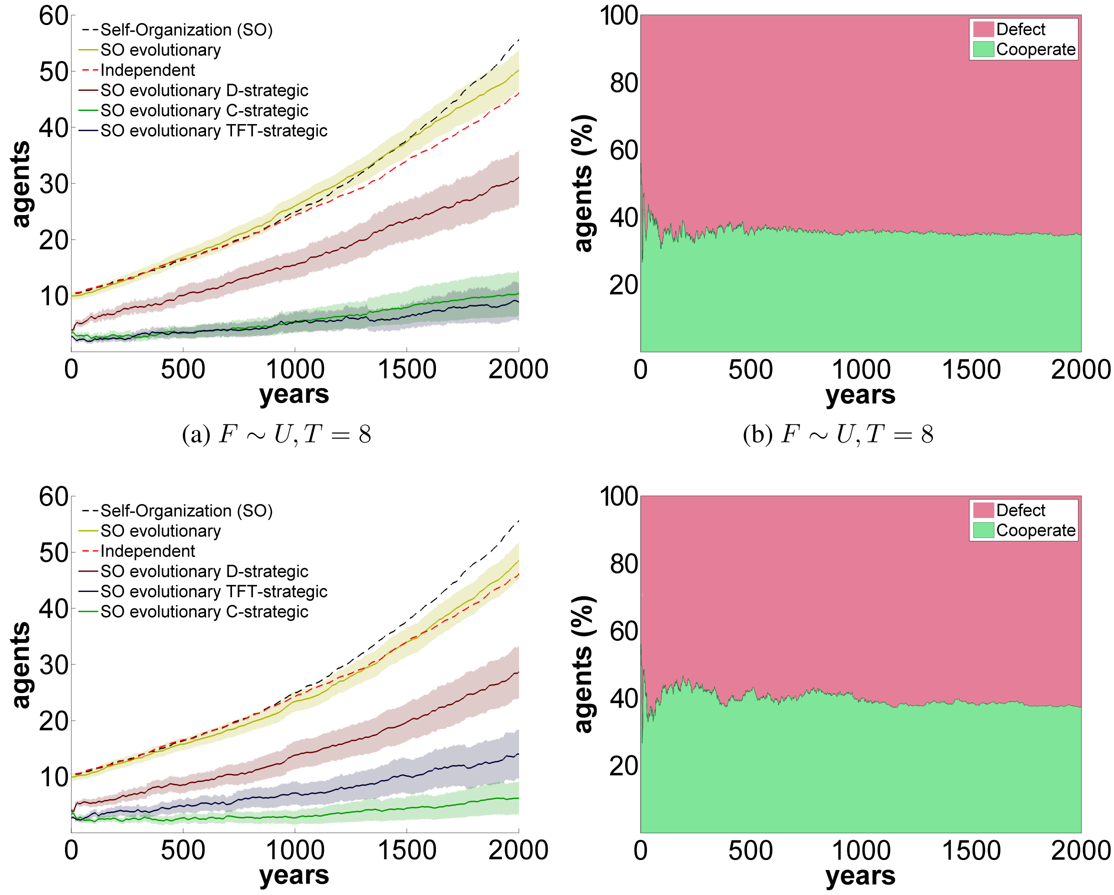
Figure 4.4: Percentage of average cooperative and defective behaviour of strategic agents (including that of TFT agents), for scenarios with *deterministic* strategy review and F calculated across *all* agents in the *settlement*.

We have also simulated scenarios where any k-strategist evaluates its strategy's performance with respect to the average fitness of the rest of k-strategists in the settlement. We do not present the corresponding figures here (*cf.* Figure B.1 in the Appendix B), since we observe a similar behaviour with the results in this category (Figure 4.3).

Strategy review wrt. society performance

In this subsection, the average organizational fitness (Equation 4.6) is evaluated by any k-strategist with respect to either the set S of all agents in the entire *society*, or the set S_k of agents in the *society* that adopt the *same strategy* as k.

When the average organizational fitness is calculated with respect to all household agents within the society and $F \sim U$ (Figure 4.5) , percentages of average defective behaviour, are slightly higher than the value observed for the corresponding scenarios of Figure 4.3, up to $\approx 65\%$, irrespective of T values. On the other hand, when $F \sim R$ (Figure 4.6) , the average "SO evolutionary" agents population is lower than the base "no strategy review" scenario (*cf.* Figure 4.2), and at most equal with the "independent" behaviour, when $T = 16$ years (Figure 4.6b). Moreover, the "SO evolutionary" agents



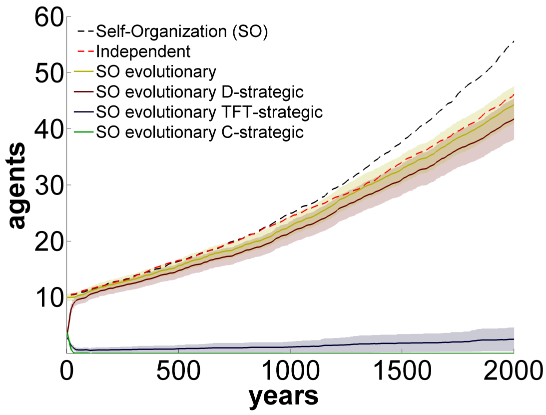
(a) $F \sim U, T = 8$ (b) $F \sim U, T = 8$

(c) $F \sim U, T = 16$ (d) $F \sim U, T = 16$

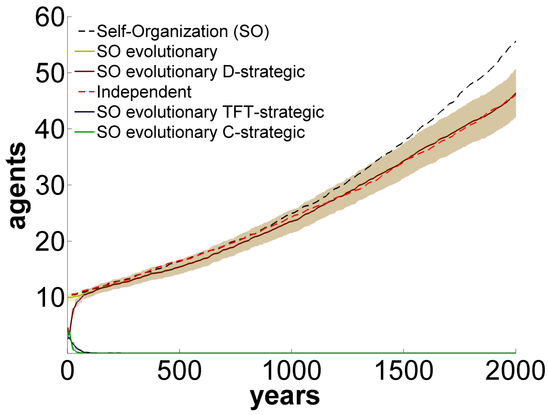
Figure 4.5: Agent population (*right*) and percentage of average cooperative and defective behaviour of strategic agents (*left*, including that of TFT agents), for scenarios with *deterministic* strategy review and $F \sim U$ calculated across *all* agents in the *society*.

are mostly D-strategists or TFT-strategists that adopt defective actions. However, when agents review their strategy more frequently, *i.e.*, $T = 8$ years (*cf.* Figure 4.6a), we report that a small fraction ($\approx 5\%$) of TFT-strategists adopt, on average, a cooperative behaviour rather than a totally defective one observed in the corresponding scenarios of Figures 4.6b, 4.3b and 4.3d, where $F \sim R$.

Moreover, percentages of average cooperative behaviour of strategic agents appear to be slightly higher when agents evaluate their fitness with respect to the average fitness of household agents in the settlement rather than the entire society and $F \sim U$ (*cf.*



(a) $F \sim R, T = 8$



(b) $F \sim R, T = 16$

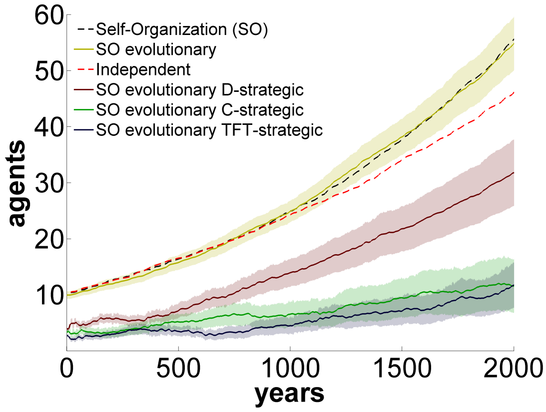
Figure 4.6: Agent population for scenarios with *deterministic* strategy review and $F \sim R$ calculated across *all* agents in the *society*.

Figures 4.4 and 4.5). This is interesting, and somewhat reassuring, since it does not seem realistic that agents would have had information about the strategic views of household agents in other settlements, for the period under study.

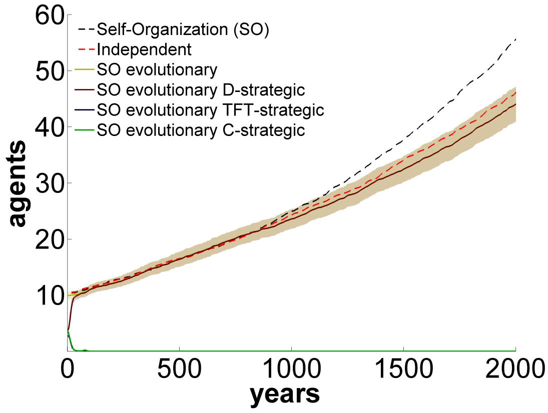
Simulation results where a k-strategist considers the set S_k of k strategic agents within the organization for fitness evaluation are presented in Figure 4.7.

We observe that average population of "SO evolutionary" agents are similar to the previous scenarios category (*cf.* Figure 4.5). When $F \sim U$, the percentage of average defective behaviour (including that of the TFT-strategists) is similar with the previous scenarios of Figure 4.5, ranging from $\approx 65\%$ up to $\approx 70\%$. Specifically, we observe a significantly lower average numbers of C-strategists in comparison with the previous corresponding scenario (Figure 4.5), and even lower when $T = 16$ (Figure 4.7c).

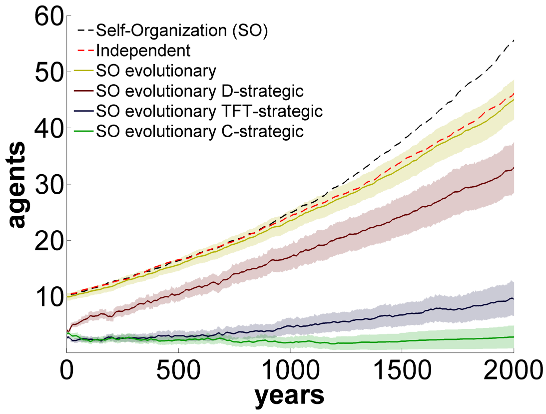
By contrast, when $F \sim R$, although average population of "SO evolutionary" agents is similar to the previous scenarios category (*cf.* Figure 4.7b), when $T = 16$ years (*cf.* Figure 4.7d), corresponding average number of agents is noticeably higher than before (and where all strategic agents defect).



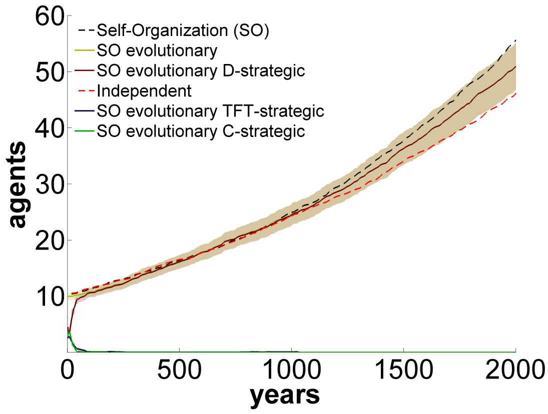
(a) $F \sim U, T = 8$



(b) $F \sim R, T = 8$



(c) $F \sim U, T = 16$



(d) $F \sim R, T = 16$

Figure 4.7: Agent population for scenarios with *deterministic* strategy review and F calculated across agents in the *society* that share the *same strategy*.

As a final note, we report that "SO evolutionary" agents are able to sustain higher average population size with respect to the previous scenarios category (*cf.* Figure 4.3), and even *higher* than the first scenario (*cf.* Figure 4.2), when $T = 8$ years and $F \sim U$ (*cf.* Figures 4.5a and 4.7a).

4.4.3 Stochastic strategy review

From this point onwards, we simulate scenarios as before, with the difference that now agents review their strategy k and *stochastically* switch to strategy l with a probability $p_{kl},\ k, l \in K$, based on the percentage of l-strategic agents in the organization (*cf.* Equation 4.7).

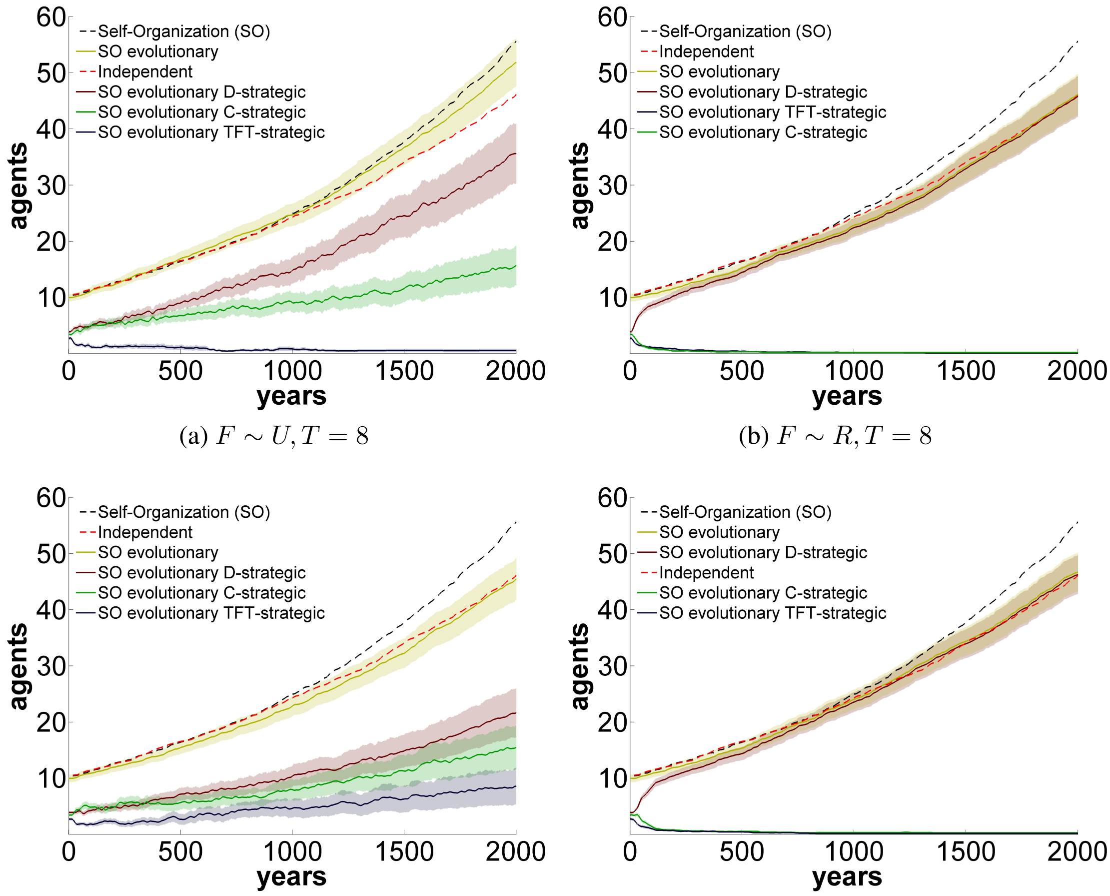
Strategy review wrt. settlement performance

In Figure 4.8, we present simulation results for scenarios where the agents review their strategy stochastically, while evaluating the average fitness of all strategic agents in the *settlement* organization.

When $F \sim U$, we observe an slight increase in the average number of agents adopting a *cooperative* strategy with respect to the corresponding scenarios of Figure 4.3, where agents review their strategy deterministically. Specifically, when $T = 16$ years, the average numbers of D-strategists decrease contrariwise (Figure 4.8c). Moreover, the average numbers of TFT-strategic agents is observed to have declined.

We also report that agents in the model adopt, on average, a cooperative behaviour (including that of the TFT-strategic agents) of $\approx 35\%$ and $\approx 50\%$ per time step, for review time periods $T = 8$ and $T = 16$ years respectively, when $F \sim U$, rather than a totally defective behaviour when $F \sim R$. In general though, the average population of "SO evolutionary" agents is again lower than in the first scenario (*cf.* Figure 4.2a), except when agent review their strategy more often and $F \sim U$ (*cf.* Figure 4.8a).

Simulation results for the scenarios where k-strategists evaluate their current performance considering the set of S_k agents within the settlement are shown in Figure 4.9. We observe a dramatic decline on the average numbers of D-strategists, irrespective of review time periods and agent fitness function calculation method.



(a) $F \sim U, T = 8$

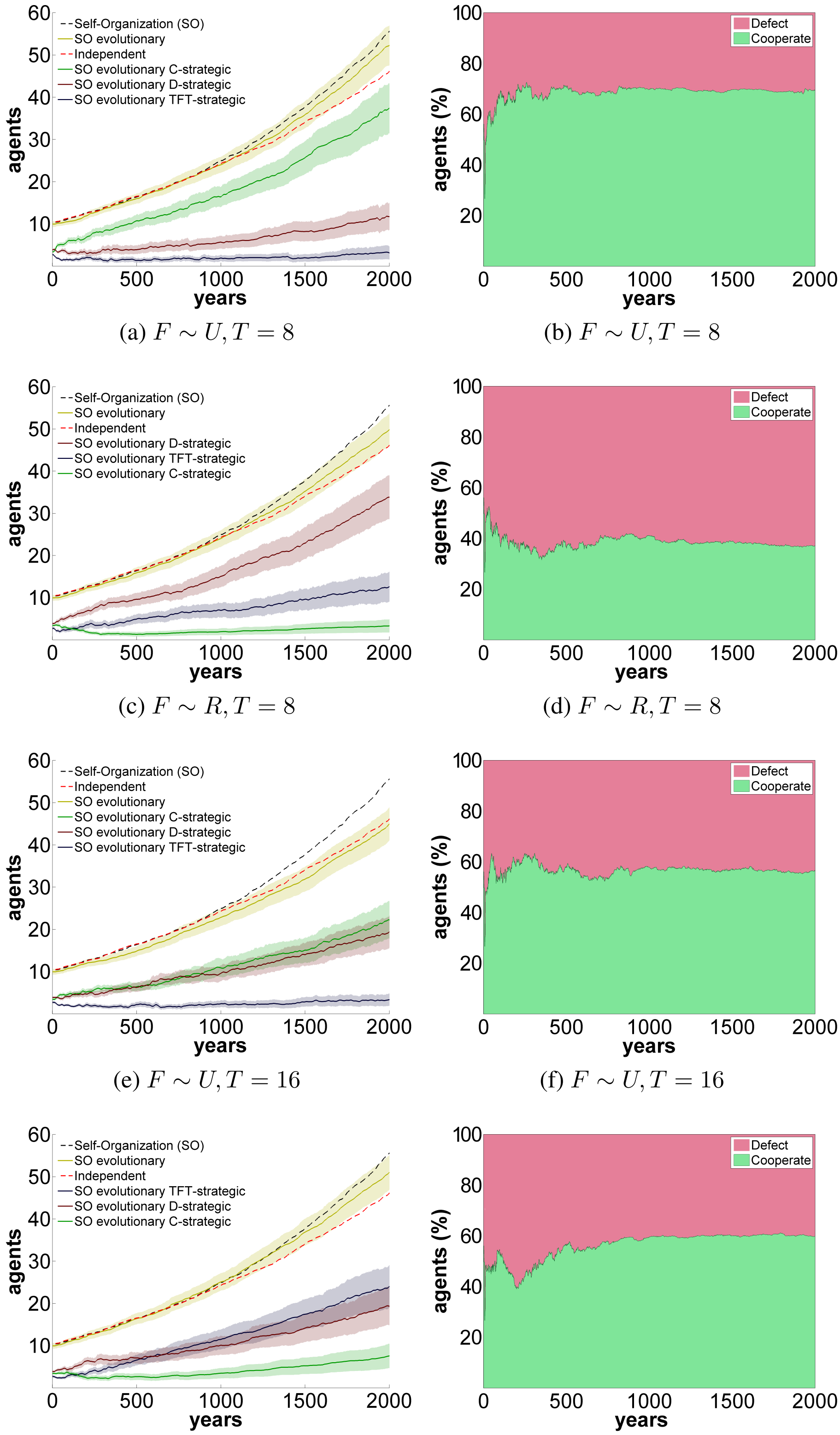
(b) $F \sim R, T = 8$

(c) $F \sim U, T = 16$

(d) $F \sim R, T = 16$

Figure 4.8: Agent population for scenarios with *stochastic* strategy review and F calculated across *all* agents in the *settlement*.

Interestingly, agents in these scenarios present the highest rates of cooperative behaviour observed, $\approx 55 - 70\%$ and $\approx 40 - 60\%$ when $F \sim U$ and $F \sim R$ respectively. When $F \sim U$, we observe a dramatic increase on the average number of C-strategists, especially when $T = 8$ years (*cf.* Figure 4.9a). Likewise, when $F \sim R$, a remarkable increase on the average number of TFT-strategists is observed, especially when $T = 16$ years (*cf.* Figure 4.9g); although TFT-strategists constitute $\approx 25\%$ and $\approx 50\%$ of the overall agent population when $F \sim R$ and $T = 8$ and $T = 16$ years respectively, they adopt on average a cooperative behaviour by $\approx 95 - 100\%$.



(a) $F \sim U, T = 8$ (b) $F \sim U, T = 8$

(c) $F \sim R, T = 8$ (d) $F \sim R, T = 8$

(e) $F \sim U, T = 16$ (f) $F \sim U, T = 16$

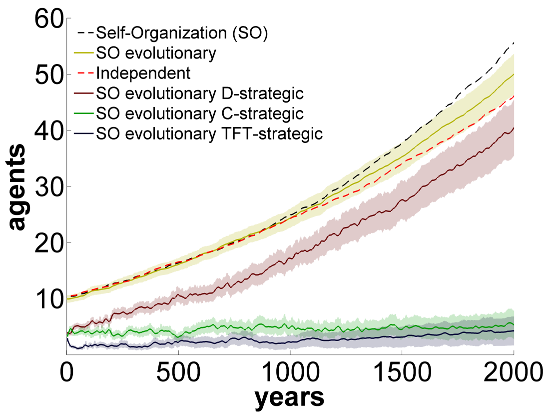
(g) $F \sim R, T = 16$ (h) $F \sim R, T = 16$

Figure 4.9: Agent population (*right*) and percentage of average cooperative and defective behaviour of strategic agents (*left*, including that of TFT agents), for scenarios with *stochastic* strategy review and F calculated across agents in the *settlement* that share the *same strategy*.

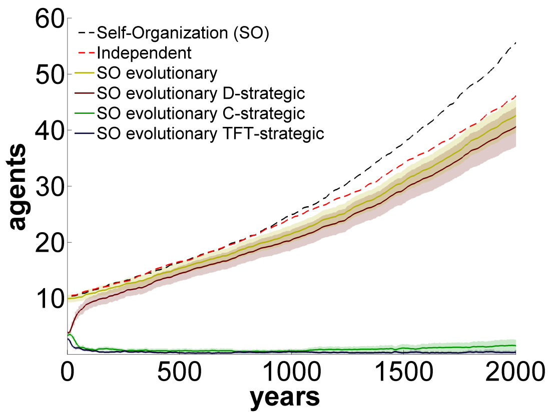
We note that the highest average population of “SO evolutionary” households and rates of cooperation behaviour among the agents, across all simulated scenarios, appears in this case—and in particular in the scenario of Figure 4.9a.

Strategy review wrt. society performance

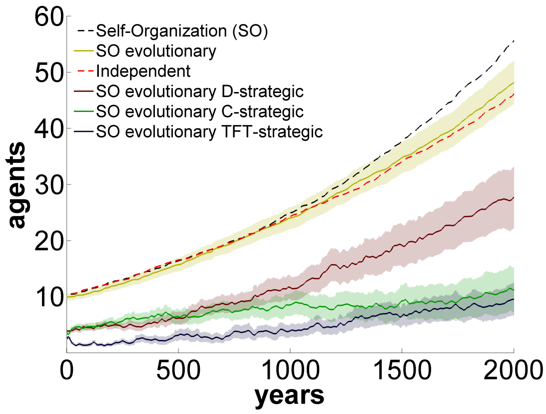
Here agents again switch their strategy stochastically, but first evaluate their performance with respect to the average performance of the *society*; they initially consider *all* agents instead of the ones only within their settlement. Results are shown in Figure 4.10.



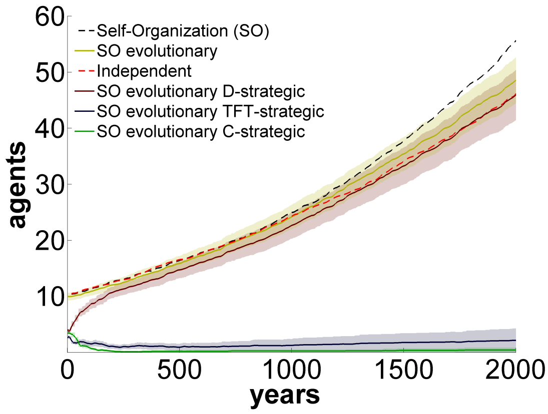
(a) $F \sim U, T = 8$



(b) $F \sim R, T = 8$



(c) $F \sim U, T = 16$



(d) $F \sim R, T = 16$

Figure 4.10: Agent population for scenarios with *stochastic* strategy review and F calculated across *all* agents in the *society*.

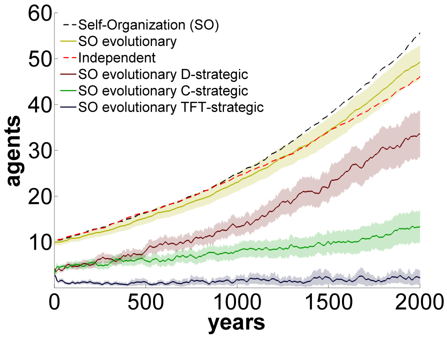
We observe that average number of "SO evolutionary" agents for scenarios where $F \sim U$ is similar to the one of the "no strategy review" scenario (Figure 4.2), especially when $T = 8$ years; in this case, we also observe the lowest percentages of average cooperative behaviour, that is $\approx 25\%$ (*cf.* Figure 4.10a).

By contrast, the average population size of strategic agents for scenarios where $F \sim R$ is much lower and similar to the "independent" social paradigm's, and even lower when $T = 8$ (*cf.* Figure 4.10b). Interestingly, while a totally defective behaviour is observed to be adopted for scenarios when $F \sim R$ and agents review their strategy with respect to the settlement performance (*cf.* Figure 4.8), here emergent cooperative behaviour is observed and adopted on average by $\approx 5 - 10\%$ of the agents.

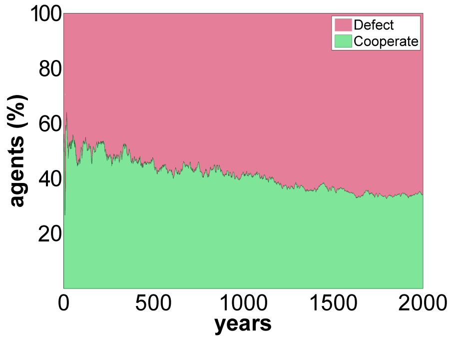
Results for scenarios where k-strategists consider the set of S_k agents within the society for their fitness evaluation, are shown in Figure 4.11. We observe similar average population sizes with the corresponding scenarios of the previous category (Figure 4.10). Interestingly, when $F \sim U$ (Figure 4.11b and 4.11f), the percentages of average cooperative behaviour (including that of the TFT-strategic agents) increase (up to $\approx 35 - 45\%$) with respect to the scenarios of the Figure 4.10; in contrast with scenarios when $F \sim R$, corresponding percentages of average cooperative behaviour are increased, from $\approx 5 - 10\%$ up to $\approx 15 - 25\%$ for review time periods $T = 16$ and $T = 8$ years respectively.

4.4.4 Discussion

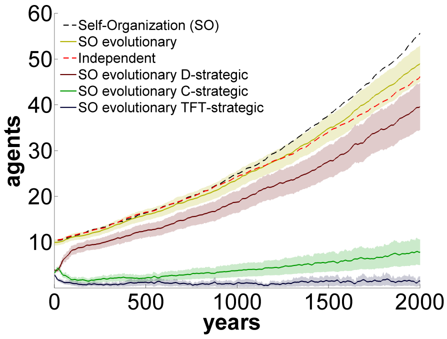
We can report that cooperative behaviour is emergent in 24 out of the 33 scenarios, with highest average rates observed when agent interactions are local and updating is stochastic, as shown in Table 4.2. Cooperation is more prevalent when $F \sim U$ rather than $F \sim R$. This is quite natural: one expects agents that evaluate fitness taking into account their *reward* in games only, to tend to become more aggressive or opportunistic; while taking into account their overall *utility* tends to smoothen such behaviours.



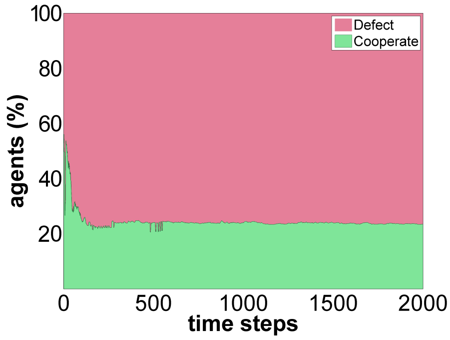
(a) $F \sim U, T = 8$



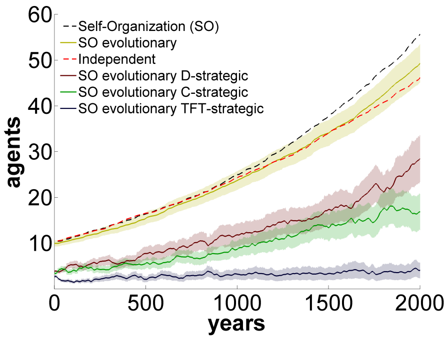
(b) $F \sim U, T = 8$



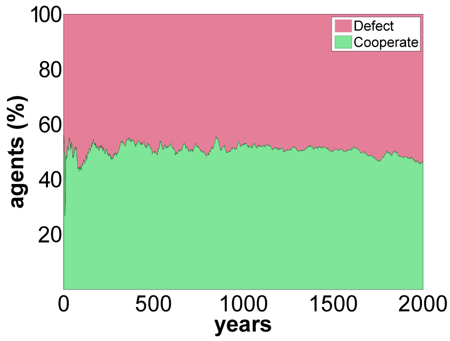
(c) $F \sim R, T = 8$



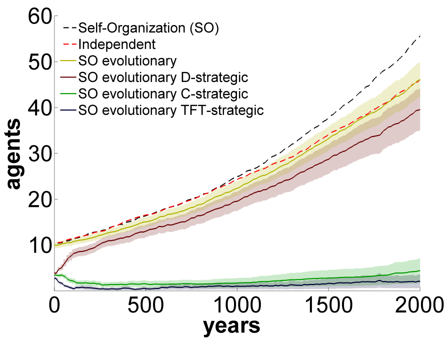
(d) $F \sim R, T = 8$



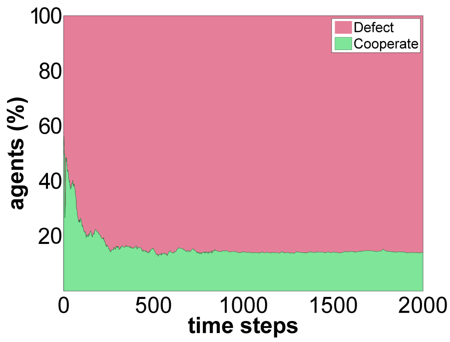
(e) $F \sim U, T = 16$



(f) $F \sim U, T = 16$



(g) $F \sim R, T = 16$



(h) $F \sim R, T = 16$

Figure 4.11: Agent population (*right*) and percentage of average cooperative and defective behaviour of strategic agents (*left*, including that of TFT agents), for scenarios with *stochastic* strategy review, and F calculated across agents in the entire *society* that share the *same strategy*.

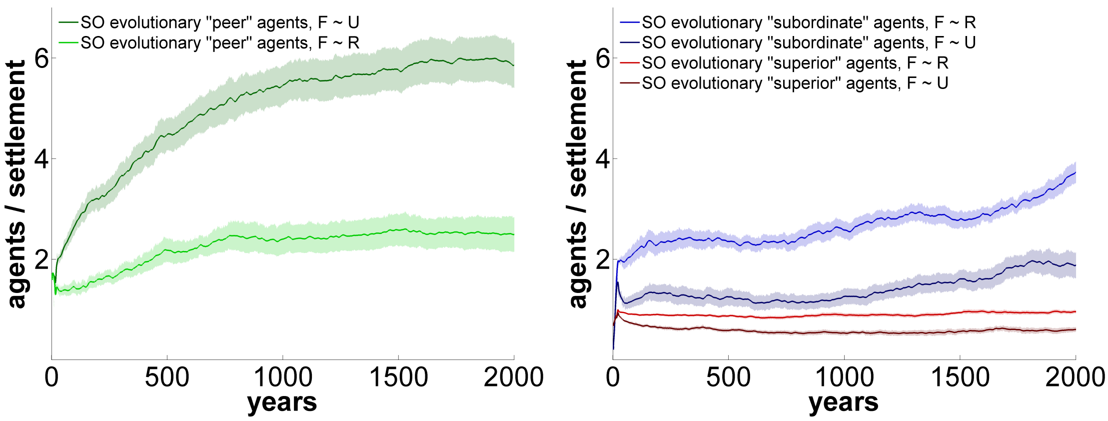
Cooperation rates (%)	Deterministic				Stochastic			
	Group		Society		Group		Society	
	S	S_k	S	S_k	S	S_k	S	S_k
$F \sim U, T = 8$	38	37	35	37	34	**70**	24	34
$F \sim U, T = 16$	44	25	37	27	49	**56**	42	46
$F \sim R, T = 8$	0	0	7	0	0	**37**	10	23
$F \sim R, T = 16$	0	2	0	0	0	**60**	7	14

Table 4.2: Average cooperative behaviour rates for all scenarios, where every k-strategist considers either the set S_k of k-strategists or the set S of *all* agents within the *settlement* organization or the entire *society*, reviewing its strategy either *deterministically* or *stochastically*.

Moreover, since the non-strategic, cooperation-oriented “self-organizing” agents, and the non-interacting, “independent” agents, can be viewed as constituting two near-extremes in terms of strategic behaviour, it is expected that the average aggregate population of the strategic agents will lie largely between their corresponding ones; indeed, simulation results confirm this intuition. Furthermore, when $F \sim U$, the error shading areas for the “SO evolutionary” lines overlap with 13 out of 16 of the “SO” ones towards the end of the simulation (last 500 years), and with 9 out of 16 of the “SO” lines, when $F \sim R$. Therefore, in many cases strategic populations can do even better than non-strategic ones. Moreover, we can report that average numbers for *settlements* and *agents per settlement* for the “evolutionary self-organization” social paradigm are approximately 5 and 12, respectively, which are similar to the ones of the “simple” self-organization one, approximately 6 and 12, respectively (*cf.* Figure 3.9 in Section 3.4).

Overall, scenarios that sustain a higher average population of “SO evolutionary” agents, are mainly those where agent fitness is evaluated with respect to their *utility*. This choice of conditioning strategy evolution on overall utility rather than reward is justified from the results, while it does make sense from a socio-economic perspective: you choose how much to “exchange” based on your overall well-being. Better performance is observed when agent fitness is evaluated to that of the *settlement* group, rather than the entire society, with respect to the average fitness (corresponding to utility) of only agents adopting the agent's current strategy; and the adoption of an alternative strategy is stochastic. In addition, percentages of average cooperative behaviour of strategic agents are higher when agents evaluate their fitness with respect to the average fitness of household agents in the settlement rather than the entire society; as mentioned earlier, this is reassuring in the sense that, agents would have had incomplete information about the strategic views of other household agents in other settlements, for the period under study. Notably, however, the scenario with high percentages of emergent cooperative behaviour also appears better in sustaining higher agents population (*cf.* Figure 4.9a).

We also report that the resulting social structure is indeed correlated with the agents' strategic behaviour. In Figure 4.12, we report that the number of *peer* related agents are higher on average when $F \sim U$, while the number of *superior* or *subordinate* agents are higher on average when $F \sim R$. This is quite expected, since when $F \sim U$ agents are more cooperative, rendering the differences in utility among them less acute—and thus the *authority* relations are fewer in that case.



(a) Peer relation (b) Authority relation

Figure 4.12: Average number of *(a) peer* and *(b) authority* related agents per settlement for scenarios where $F \sim U$ and $F \sim R$, over 2,000 (yearly) time steps.

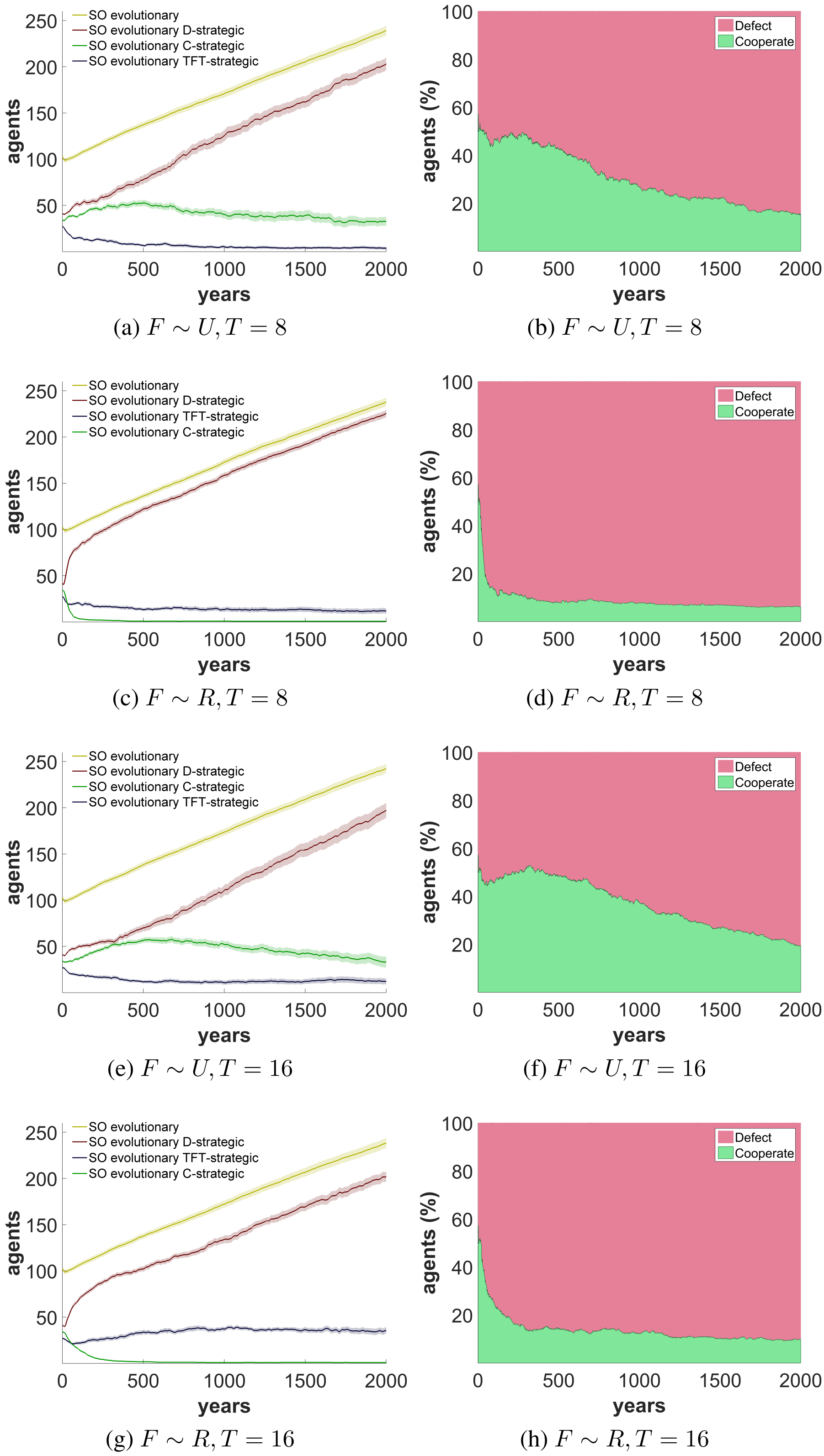
4.4.5 Sensitivity analysis

In this section we apply a *sensitivity analysis* process to determine how sensitive our ABM is to the particular set of initial conditions that we used. Specifically, we examine the impact of varying the model parameters on model results. Specifically, recall that we considered an initial number of approximately 10 agents on average in the model environment (*cf.* Section 3.3.1), and a uniform distribution of initial strategies. We wish to investigate if a higher initial agent population and a different initial distribution of strategies will affect the results. We also wish to examine whether adding some *randomness* on agent behaviours affects simulation results. To this purpose, we re-ran all experiments in Section 4.4, changing initial conditions or adding randomness. However, we restrict our presentation to scenarios of Figure 4.9—*i.e.*, scenarios with stochastic strategy review and F calculated across agents in the *settlement* that share the *same strategy*, since these were shown to sustain a higher agent population size and higher percentage of emergent cooperative behaviour (*cf.* Table 4.2).

Number of agents

Our simulation experiments involve an initial average population of 100 agents. Simulation results of agent population for the corresponding scenarios of Figure 4.9 are shown in Figure 4.13.

We now observe that, when $F \sim U$, agents adopt lower rates of average cooperative behaviour, from $\approx 55 - 70\%$ (*cf.* Figures 4.9b and 4.9f) down to $\approx 15 - 20\%$ (Figures 4.13b and 4.13f). In scenarios where $F \sim R$, the adopted average cooperative behaviour is further reduced down to $\approx 5 - 10\%$ (Figures 4.13d and 4.13h) from $\approx 40 - 60\%$ (*cf.* Figures 4.9d and 4.9h). Interestingly, we report that when $F \sim R$, TFT-strategists drop down to $\approx 5 - 15\%$ from $\approx 25 - 50\%$ (*cf.* Figures 4.9c and 4.9g) of the overall agent population (for $T = 8$ and $T = 16$ years respectively). Additionally, they also exhibit lower rates of cooperative behaviour (from $\approx 95\%$ down to $\approx 65\%$).



(a) $F \sim U, T = 8$ (b) $F \sim U, T = 8$

(c) $F \sim R, T = 8$ (d) $F \sim R, T = 8$

(e) $F \sim U, T = 16$ (f) $F \sim U, T = 16$

(g) $F \sim R, T = 16$ (h) $F \sim R, T = 16$

Figure 4.13: Agent population of initially 100 agents (*right*) and percentage of average cooperative and defective behaviour of agents (*left*, including that of TFT-strategists), for scenarios with *stochastic* strategy review and F calculated across agents in the *settlement* that share the *same strategy*.

Notably, however, the highest average cooperation rates and average population of "SO evolutionary" household agents, across all simulated scenarios appears in this case, similarly to the corresponding scenarios of Figure 4.9. Although we observe lower levels of corresponding average cooperative behaviour, that seem to be decreased with time, we do not anticipate that a higher initial population of agents will substantially change the conclusions drawn from our simulations here.

Distribution of strategies

In this section we shall assume an environment with initially 10 agents on average and different initial distribution of strategies. We conduct three different sets of experiments, each one with different initial distribution of strategies, giving higher rates to each one of the assumed agent strategic behaviours.

For the first set of experiments we assume an initial distribution of 90% C-strategists, 10% D-strategists and 10% TFT-strategists. Intuitively, we expect higher rates of average cooperative behaviour, since agents in the corresponding scenarios of Figure 4.9 adopt the highest ones observed in our simulations. Indeed, we observe that agents in these scenarios adopt higher rates of average cooperative behaviour; however, the average populations of "SO evolutionary" household agents are in the same range as the ones in the corresponding simulation scenarios. Simulation results for the respective scenarios are not shown here, but can be found in the Appendix B (Figure B.2)

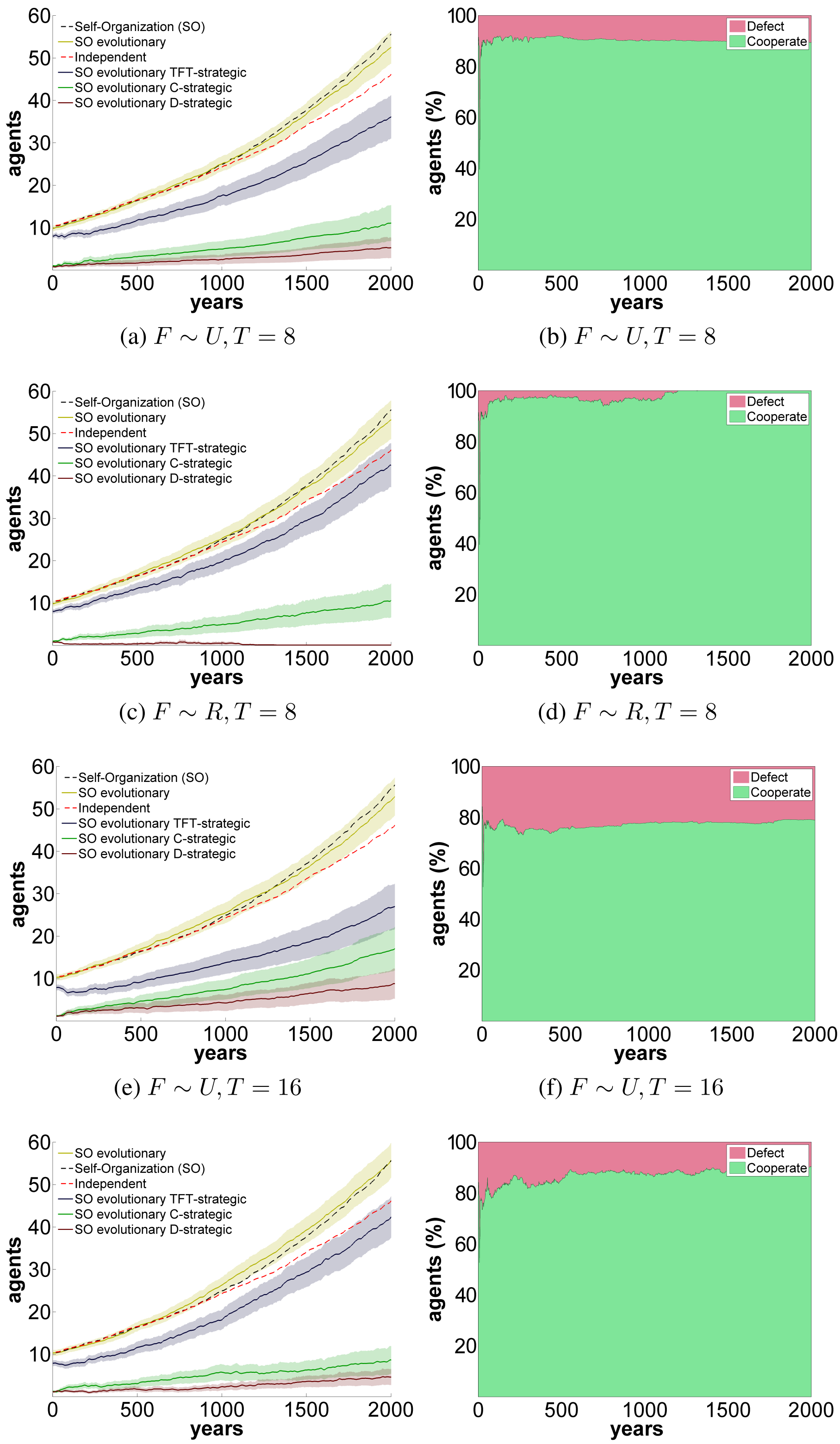
For the second set of experiments we assume an initial distribution of 90% D-strategists, 10% C-strategists and 10% TFT-strategists. Naturally, we now expect lower rates of cooperative behaviour (and, accordingly, higher rates of defective behaviour). Indeed, agents in these scenarios adopt lower cooperative behaviour than the corresponding scenarios of Figure 4.9; simulation results for these scenarios can be found in the Appendix B (Figure B.3). Again, we observe that the average populations of "SO evolutionary" household agents for these scenarios are in the same range as the ones of the corresponding scenarios.

For the last set of experiments here, we assume an initial distribution of 90% TFT-strategists, 10% D-strategists and 10% C-strategists. Now, TFT strategy is an effective technique for reducing conflict within a population and can be successful, provided that some necessary conditions apply; being nice, retaliating, forgiving and non-envious [5]. Since the optimal strategy for an agent depends on its initial popularity (and on the length of the game), the specific experimental setting (favouring TFT) establishes very favourable conditions under which cooperation in the simulated society based on reciprocity may emerge and evolve. Simulation results for these scenarios are shown in Figure 4.14. We report that agents now adopt a cooperative behaviour that is even higher than the corresponding scenarios of Figure 4.9.

Interestingly, the average populations of "SO evolutionary" agents are remarkably higher than the ones of the corresponding scenarios of Figure 4.9, irrespective of review time periods and agent fitness function calculation method. We note that the population growth rate achieved by the 'SO evolutionary" household agents for the scenarios of Figure 4.14 is on average 0.083%, a very high rate that is both higher than the one achieved by the "SO" agents, which was 0.077%, and also closer to 0.1%, which is the maximum growth rate considered in our simulations (*cf.* Section 3.1.3).

Randomness

In this section we again simulate agents with the same setup as in the scenarios of Figure 4.9; however, while an agent, when facing another in a game, still selects an exchange behaviour that is in line with its strategy, there is now a possibility of randomly selecting the *opposite* (cooperative or defective) behaviour than the one currently defined by its strategy. This somewhat mirrors situations where agents "make mistakes" or have "a trembling hand" [51]. We conduct two different sets of experiments, one with lower (20%) and one with higher (40%) *error rates*, signifying the probability of selecting the opposite *action* (of course, the *strategy* of the agent remains unaltered).



(a) $F \sim U, T = 8$ (b) $F \sim U, T = 8$

(c) $F \sim R, T = 8$ (d) $F \sim R, T = 8$

(e) $F \sim U, T = 16$ (f) $F \sim U, T = 16$

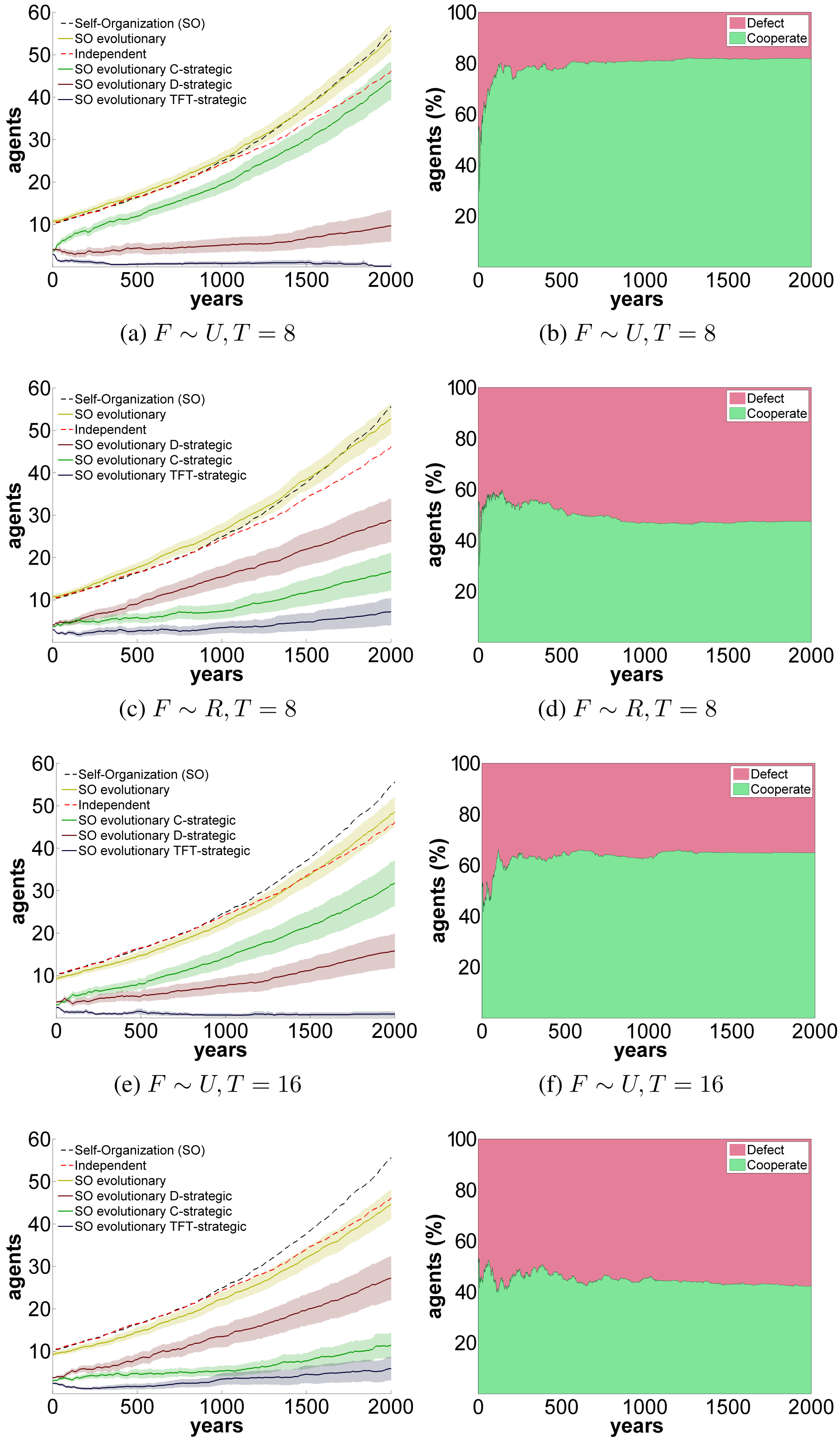
(g) $F \sim R, T = 16$ (h) $F \sim R, T = 16$

Figure 4.14: Agent population (*right*) and percentage of average cooperative and defective behaviour of strategic agents (*left*, including that of TFT agents), for scenarios involving an initial rate of 90% of TFT-strategists, with *stochastic* strategy review and F calculated across agents in the *settlement* that share the *same strategy*.

In simulation scenarios with 20% error rate, we observe that when $F \sim U$, the "SO evolutionary" household agents are able to achieve slightly higher population sizes on average than the ones of the corresponding scenarios of Figure 4.9, and with somewhat higher average rates of cooperation behaviour. By contrast, when $F \sim R$, we observe that agents adopt remarkably higher rates of defective behaviour than the corresponding scenarios of Figure 4.9, and there is a lower average number of "SO evolutionary" household agents, similar to the "independent" behaviour mean population size. Simulation results for these scenarios can be found in the Appendix B (Figure B.4).

For the second set of experiments, we adopt a 40% error rate. Simulation results for these scenarios are shown in Figure 4.15. When $F \sim U$, we observe that the average population sizes of "SO evolutionary" household agents are somewhat in the same range with the ones of the corresponding scenarios of Figure 4.9. We also report a lower average number of TFT-strategists and a higher average number of C-strategists, particularly when $T = 8$ years, thus, rendering higher average cooperation rates from $\approx 60\%$ up to $\approx 80\%$. When $F \sim R$, and particularly when $T = 16$ (Figure 4.15g), we observe a low average number of "SO evolutionary" agents, even lower than the "independent" behaviour mean population size. In addition, while the average number of C-strategists is the same as in the corresponding scenario (*cf.* Figure 4.9g), we observe a lower average number of TFT-strategists and a higher average number of D-strategists.

Overall, however, adding more or less randomness "uniformly" in agent actions does not appear to significantly affect our simulation results, since rates of average cooperative behaviour of strategic agents exhibit the same trend with the ones of the corresponding scenarios of Figure 4.9, that is, lower when $F \sim R$ and higher when $F \sim U$, respectively. However, there is a perceived difference of average agent population; we observe a slightly higher average number of agents when $F \sim U$, while when $F \sim R$, and in particular when $T = 16$ (*cf.* Figure 4.15g), the average population size of "SO evolutionary" agents drops by $\approx 15\%$ with respect to average agent population for the corresponding scenario of Figure 4.9g.



(a) $F \sim U, T = 8$ (b) $F \sim U, T = 8$

(c) $F \sim R, T = 8$ (d) $F \sim R, T = 8$

(e) $F \sim U, T = 16$ (f) $F \sim U, T = 16$

(g) $F \sim R, T = 16$ (h) $F \sim R, T = 16$

Figure 4.15: Agent population (*right*) and percentage of average cooperative and defective behaviour of strategic agents (*left*, including that of TFT agents), with 40% error rate on action selection for scenarios with *stochastic* strategy review and F calculated across agents in the *settlement* that share the *same strategy*.

4.5 Conclusions

Building on key EGT concepts, in this chapter we simulated a series of repeated games with *non-static* payoffs, played among a finite but not *constant* population of autonomous strategic agents, representing Minoan "households". In particular, we simulated the households' behavioural evolution when interacting by *exchanging resources* among themselves by assuming that exchanges are modeled via two-player games, and considering various scenarios and initialization setups. The strategic agent interactions, and their effects on agent utility, drive the continuous re-organization of the social structure, and naturally lead to the survival of the most successful strategies. The focus on agent, rather than strategy, fitness, is a departure from "standard" EGT, and allows us to deal with problems like the one here.

Our results indicate that scenarios that are better in sustaining higher agents population are those at which agents adopt new strategies in a stochastic manner and agent performance is compared to that of their immediate community—especially to that of agents in the group that adopt the same strategic behaviour—rather than the entire society. In these scenarios, agent populations converge to adopting cooperative strategies, despite this behaviour being in contrast to that prescribed by the stage game Nash equilibrium. Furthermore, results are in line with the view that, though complex societies emerge to a large extent due to conflict and competition, these social conditions seldom exist without cooperative agreements, alliances and cooperation networks in societies [118, 58].

Chapter 5

Incorporating a Natural Disaster component

In this chapter we further extent our ABM system by employing a natural disaster component for simulating the effect of such a catastrophe on the social organization of an artificial past society. In particular, we study the extent by which the cataclysmic volcanic eruption of Thera (Santorini) impacted the Minoan social evolution. Considering agriculture as the main production activity sustaining the human population, we evaluate the volcanic eruption impact on "household" agents social organization, focusing on the wider area of *Malia* region at the island of Crete.

Results over a number of different simulation scenarios demonstrate that household agents are able to sustain themselves after the natural catastrophe event. However, in some scenarios we observe noticeable changes in the settlements' distribution, relating to significantly higher migration rates immediately after the eruption. Moreover, the eruption appears to have had a strong impact on social behaviour, transforming the initially cooperative agents' behaviour to a non-cooperative one. This provides support for archaeological theories suggesting that the Theran eruption led to an apparent breakdown of the Minoan socio-economic system, partly due to inner community competition and conflicts.

Our work in this chapter provides certain contributions, also illustrated in Figure 5.1 below:

- We incorporate spatial analysis techniques to our data model, towards the development of a simple natural disaster module representing a volcanic eruption catastrophe, able to also capture associated sudden-onset and slow-onset disasters.
- We employ a natural disaster module into archaeological agent-based simulations for assessing the imminent social crisis in terms of agents social structure adaptation, agent community numbers and sizes, migration behaviour and agents strategic behaviour evolution, before and after a natural catastrophe event.
- We conduct a systematic evaluation of several natural disaster scenarios on social change, based on archaeologically traceable environmental and human impact of the mid-2nd millennium BCE Santorini eruption to the Minoan civilization.

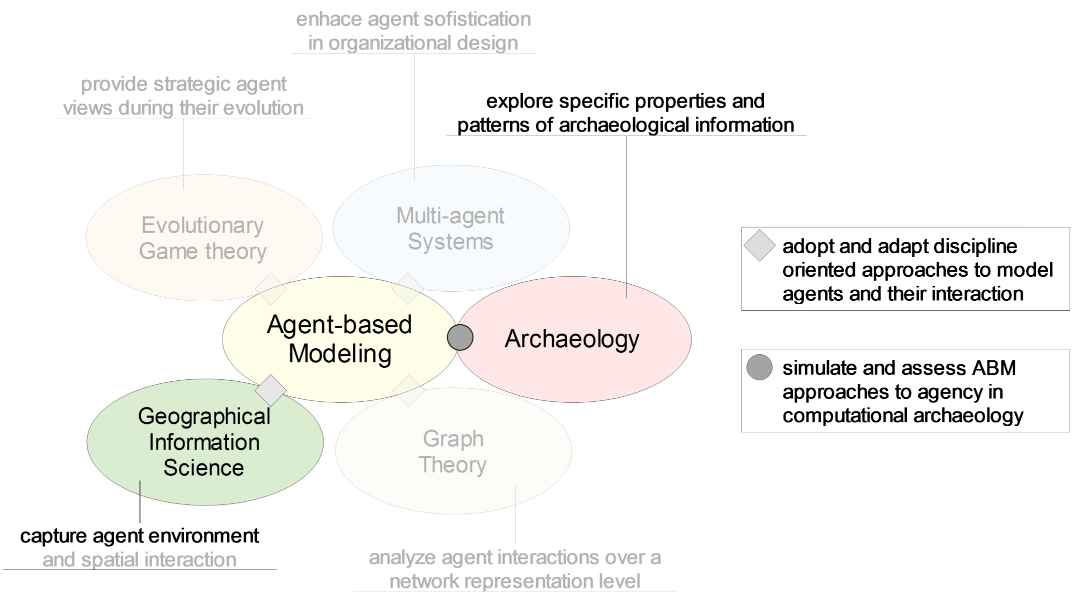


Figure 5.1: Overview of involved scientific fields and contributions in Chapter 5.

The remainder of this chapter is structured as follows. Section 5.1 provides an overview on the archaeological background regarding the natural disaster modeled, based on archaeological evidence about the volcanic eruption of Santorini island. In section 5.2 presents associated characteristics of the respective natural disaster that were taken into account for transforming the conceptual model to computational terms. Section 5.3 then records our evaluation on the impact of the simulated natural disaster on the artificial Minoan society—by first detailing the simulation parameters for the various scenarios considered, and then analysing the obtained results for our case study. Finally, Section 5.4 concludes this work by providing main outcomes of our work presented here. Parts of the research described in this chapter appeared originally in [27].

5.1 Background

As already mentioned in Section 2.5, a series of changes in the Minoan society were triggered by the LM (Late Minoan) IA or *ca.* 16th c. BCE Santorini eruption. These changes would have caused the breakdown of the Minoan system over the course of a few generations, during LM IB (15th c. BCE). Archaeologists hypothesize that the eruption would have initially caused major problems in food production and distribution, undermining central authority and leading to a process of decentralization; this fragmentation would then have led incrementally to internal conflict. However, despite the many destructions and abandonments documented, Minoan culture survived.

Moreover, there is also no doubt that during the eruption large amounts of ash and pumice were emitted. Deposits of tephra originating from the Minoan Santorini eruption have been found dispersed in many Cretan sites. However, distinct volcanic ash layers are not apparent in the open hilly landscape of Crete [17]. While ash veils from a volcanic eruption normally clear up within a few years, dendrochronological work suggests limited plant growth for up to a decade [7], rendering its impact detrimental to farms, at least on the eastern half of island of Crete.

It may further be assumed that the eruption was accompanied by one or more tsunamis [112]. Tsunami generation and simulations suggest that the north coast of Crete was struck by highly variable wave amplitudes, ranging from a few to almost 30m with inundations of up to 300m inland, considering caldera collapse [101]. However, new evidence suggests that tsunamis can only have been caused by pyroclastic flows, where reasonable estimates reach up to a maximum of 10-12m height [98].

Based on the above, we may now form and describe the conceptual natural disaster sub-model incorporated in our ABM system, in an attempt to provide insights to whether the effects of the Santorini eruption set in motion the process that led to the breakdown of Minoan society in *ca.* 1450 BCE.

5.2 Modeling the Volcanic Eruption of Thera

We assume that the natural disaster sub-model takes effect at 1630 BCE, that is, approximately the date of the eruption estimated by earth scientists [40]. In order to conceptualize the model, we considered associated sudden-onset disasters, such as *tsunami*, and slow-onset disasters, such as the *volcanic ash*, and their effects on agriculture and human life. To that end, we assume and model the following simple processes based on archaeological estimates (*cf.* previous Section 5.1):

Tsunami We assume slr meters sea-level rise (including 2m rise on today elevation), with inundations of ind meters inland in order to define tsunami-affected areas on the model's environmental grid. The agricultural impact to the respective areas is assumed to be rendering associated agricultural fields useless for up to 20 years. Human (immediate) impact is also assumed to create 10-15$\%$ fatalities (mortality) at the tsunami affected areas, linearly decreasing with distance to coastline (Figure 5.2a).

Volcanic ash Considering that the volcanic ash layer is smaller at higher elevations and clears up within 2-3 years, we assume the environmental impact of the eruption to be a limited growth to all agricultural fields in the model area for up to 10 years. The agricultural impact is considered to affect environmental cells inversely linear to elevation (Figure 5.2b). For simplicity, no immediate human impact is assumed by the volcanic ash emission process.

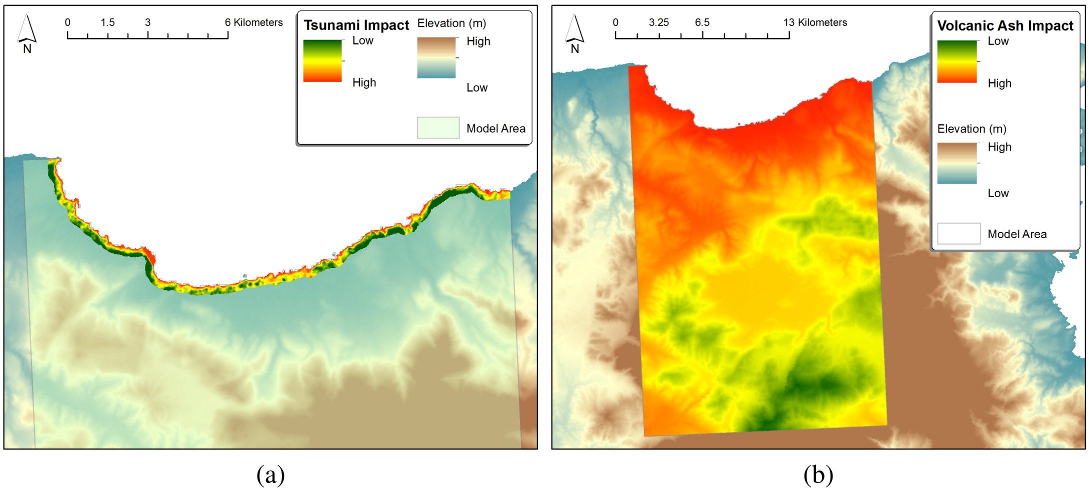


Figure 5.2: *(a)* Human impact of tsunami (sudden-onset) and *(b)* agricultural impact of volcanic ash (slow-onset) disasters in our modeling area, associated with the volcanic eruption process, incorporated in the natural disaster module.

We apply simple spatial analysis to the various environmental feature data in order to model the above processes as parts of our simple natural disaster module; results of the analysis are shown in Figure 5.2. The respective component is incorporated in our ABM system for studying and evaluating the impact of the volcanic eruption of Thera on different social organization paradigms of Minoan household agents located in the wider area of Malia at the island of Crete (see Figure 3.6).

5.3 Simulation Experiments and Results

Model parameters are initialized to values that correspond to archaeological records or estimates found in archaeological studies relevant to the period of concern *etc.* (*cf.* Section 3.3.1). Thus, in our default case volcanic eruption scenarios category, we set $slr = 10$m sea-level rise, with inundations of $ind = 300$m for the definition of the tsunami affected areas, based on archaeological estimates. We also define another 2 volcanic eruption scenarios categories, the *extreme* and the *realistic* case, as will be explained later on. In all simulation experiments below, an *intensive* agricultural regime is employed by household agents, and it is also required that agent settlements are built *near aquifer* locations. Mortality rates for the natural disaster sub-model—that is, the probability of annual deaths among household individuals located at the tsunami-affected area—were initialized to 10% and 15%. Moreover, we evaluate the performance of agents that use a *self-organized* social behaviour against those that self-organize but do not change their relations (*hierarchical*), in terms of population growth achieved.

Overall, 12 experimental scenarios were simulated, and each scenario was simulated for 30 runs, for a total of 360 simulation runs $= 30 \times 2$ (agent organization paradigms) $\times$ 3 (volcanic eruption scenarios) $\times$ 2 (mortality rates). In all figures below, we depict shaded areas that correspond to 95% confidence intervals around lines corresponding to average number of household agents, number of settlements and settlement sizes.

5.3.1 Default case scenarios

For the default case volcanic eruption scenarios, we report that average agent population size (number of households) increases with time, regardless of mortality rates, exhibiting similar viability potential for both the self-organization and hierarchical organization structures, as shown in Figure 5.3. Additionally, we observe no human losses; during simulation runs, no household agent was settled at tsunami-affected areas at the time of the eruption, where fatalities are introduced by the model.

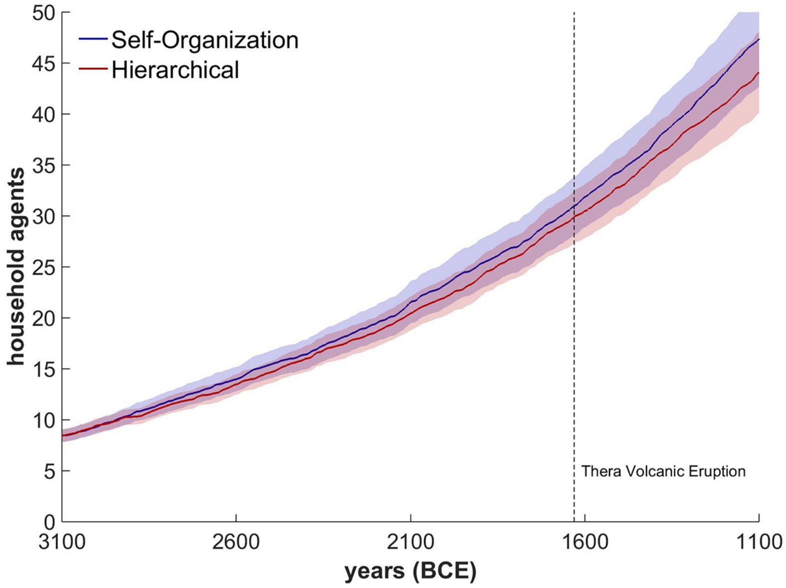


Figure 5.3: Number of household agents over 2000 (yearly) time steps for the *default* case scenario, considering 10% mortality rate.

We do observe, however, an increase of 60% on the average number of settlements (Figure 5.4). This is due to higher migration rates observed immediately after the eruption, as further stated in our observations.

Moreover, we report an overall decline of 30% on the average number of household agents per settlement after the eruption (Figure 5.5). Therefore, changes in settlement numbers and sizes are observed due to the agricultural impact of the eruption; more and smaller size settlements continue to cultivate the land after the eruption. Intuitively, one could assume that the layering of volcanic ash and the subsequent degradation of soil quality led to increased migration.

We note that, in all simulation results we resented above, the performance of the self-organized social organization paradigm appears to be (slightly) better in sustaining higher agent population and settlement sizes than the (static) hierarchical one. Moreover, simulation scenarios considering 15% mortality rate exhibit a similar behaviour,

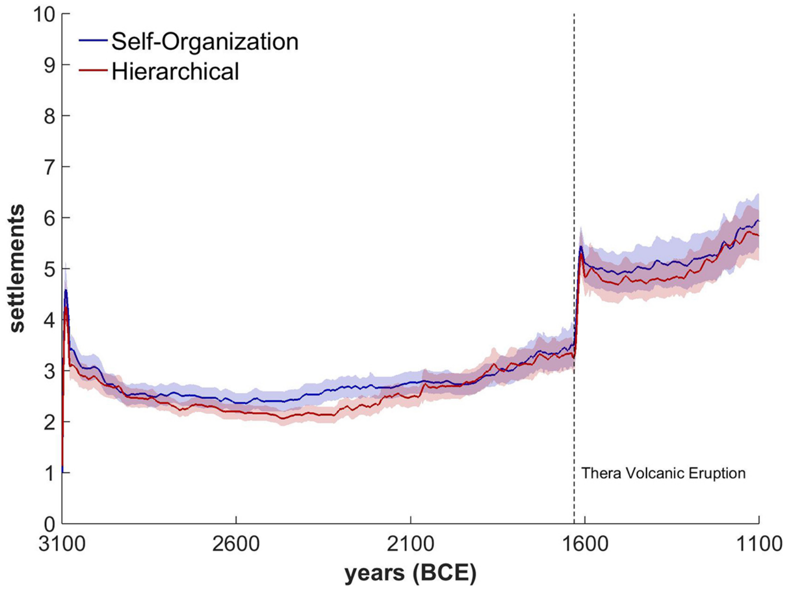


Figure 5.4: Number of agent settlements over 2000 (yearly) time steps for the *default* case scenario, considering 10% mortality rate.

thus, they are not presented here. Now, since no human losses are observed for the default case scenarios, we attempted to manually "move" (set) at the time of the eruption existing agent settlements to tsunami affected areas, in order to evaluate the human impact of the natural disaster on the artificial society. We assume the following two (2) alternative scenario cases: *(i)* moving the closest existing settlement to the geographical location of the archaeological site of *Malia*; and *(ii)* moving two (2) closest existing settlements to randomly selected tsunami affected geographical locations.

In what follows, we refer to the former scenarios category *(i)* as *extreme case* scenarios, where the impact of the tsunami waves at the archaeological settlement of Malia presupposes an unrealistic parameterization to the natural disaster sub-model; the site is located in an elevation of $slr = 18$m (wave height) and a distance from the coast $ind = 670$m (inundation). We also refer to scenarios category *(ii)* as *realistic case* scenarios, since the default setup of the natural disaster sub-model was used ($slr = 10$ and $ind = 300$). Moreover, we present simulation results where 15% mortality rate was

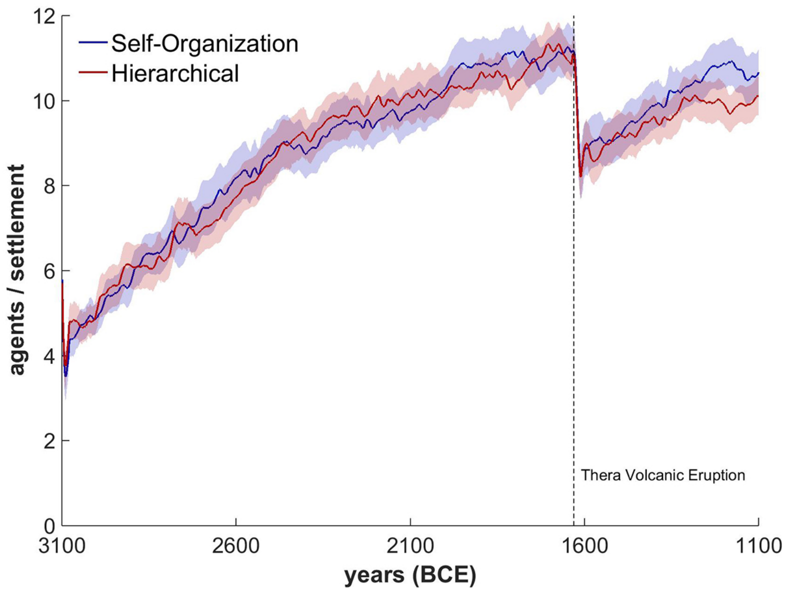


Figure 5.5: Number of agents per settlement over 2000 (yearly) time steps for the *default* case scenario, considering 10% mortality rate.

introduced and not for 10% mortality rate. In both cases, however, simulation results exhibit similar effects; nevertheless, those are more intense and noticeable for the former (15% mortality rate), and thus, discussed here.

5.3.2 Alternative scenarios

Simulation results on average household agents' population size are illustrated in Figure 5.6. We observe that agent population size is now reduced for both the self-organization and hierarchical social organization paradigms, reaching up to $\approx 8\%$ death toll for the *extreme* case scenario (Figure 5.6a) and up to $\approx 16\%$ for the *realistic* case scenario (Figure 5.6b), respectively. This is due the fact that 2 out of 3 settlements on average (over 30 runs) were struck by the tsunami waves.

By contrast, we observe an increase on the average number of settlements of $\approx 90\%$ for the *extreme* case scenario and of $\approx 150\%$ for the *realistic* case scenario, respectively, as depicted in Figure 5.7. For the *realistic* case scenario, in particular, we observe more

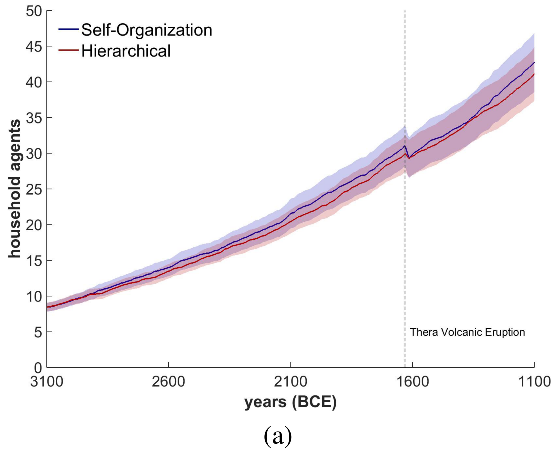


Figure 5.6: Number of agents over 2000 (yearly) time steps for *(a)* the *extreme* case scenario and *(b)* the *realistic* case scenario, considering 15% mortality rate.

settlements after the volcanic eruption for household agents adopting the self-organized social behaviour, rather than the hierarchical (static) one.

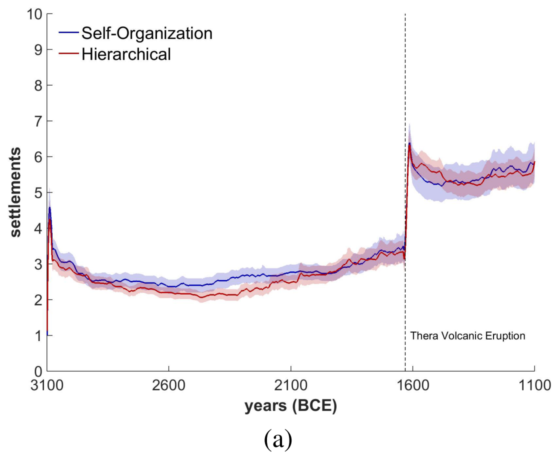


Figure 5.7: Number of settlements over 2000 (yearly) time steps for *(a)* the *extreme* case scenario and *(b)* the *realistic* case scenario, considering 15% mortality rate.

In addition, we observe an even more abrupt decline on the average number of household agents per settlement (settlement size) after the eruption, of $\approx 40\%$ for the *extreme* case scenario (Figure 5.8a) and of $\approx 55\%$ for the *realistic* case scenario (Figure 5.8b),

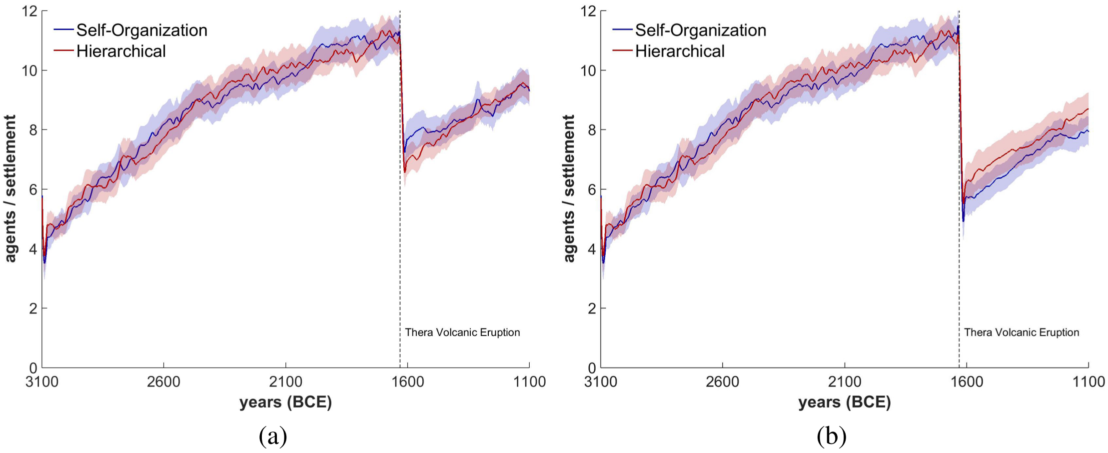


Figure 5.8: Settlement sizes over 2000 (yearly) time steps for *(a)* the *extreme* case scenario and *(b)* the *realistic* case scenario, considering 15% mortality rate.

Therefore, we observe a totally changed landscape consisting of many "small-size" settlements after the eruption rather than a few and higher in size communities before the eruption. This major change is a result of the environmental impact by the volcanic ash and pumice, as well as the human impact attributed to the tsunami waves that struck settlements located near to the coast. As a result, we observe that household agents are being "forced" to migrate to other (better) environmental areas due to impact of the natural hazard on agriculture and subsequent production damage and loss. We report that before the eruption, migration rate for the agents—that is, average number of households out of the total number of households that migrate annually to other locations—was $\approx$ 1%; while immediately after the eruption, migration rates were increased to $\approx$ 15%, $\approx$ 20% and $\approx$ 25% for the default, extreme, and realistic case scenarios, respectively.

Moreover, since household agents are able to store any surplus resources in their storage, for up to several years (default: 5), we report on the average amount of resources stored before and after the time of the eruption, in order to further examine the high migration rates and percentage of household agents being potentially "undernourished". The average amount of resources stored by household agents during the simulation period is similar for all scenarios, however, agents adopting the self-organized social behaviour appear to have an advantage on the amounts they were able to store after the volcanic eruption. In particular, storage average values drop to $\approx 95\%$ immediately after the time of the eruption; however, self-organized household agents succeed to store even more than before the eruption, after a few decades from the time of the eruption until the end of the Minoan period, while hierarchically organized agents also manage to bounce back in terms of food stored (Figure 5.9). Moreover, we observe that after the eruption, storage values are slightly higher for agents adopting a self-organized social behaviour than agents employing a static hierarchical social paradigm.

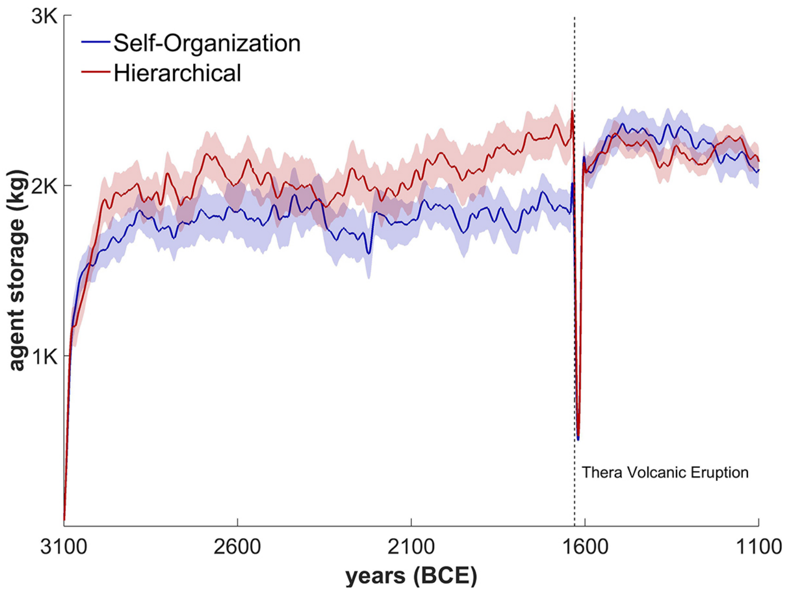


Figure 5.9: Agent average storage over 2000 (yearly) time steps for the *realistic* case scenario, considering 15% mortality rate.

Certainly, the impact of a natural disaster on a human society tends to affect also aspects of its community life, since essential functions of the society (such as the allocation of resources) are interrupted or destroyed. Therefore, in order to assess the social crisis potentially caused by the volcanic eruption impact on the artificial society, we also provide simulation results employing our alternative agent self-organization social paradigm that is driven by the interactions of strategic agents operating within a given social organization group, as described previously in Chapter 4.

5.3.3 Social impact

We simulate additional scenarios, considering that the agents employ an “evolutionary” self-organization social paradigm; however, the number of initial settlements are now set to 20. In this way the evolution of strategic agents’ behaviour during the simulation can be better observed. To this end, we evaluate the performance of agents that play games and self-organize, in terms of population growth achieved.

In particular, we examine the evolutionary self-organization social behaviour setting that was able to achieve the most cooperative behaviour observed. In the previous chapter, we have shown that agent populations converge to adopting cooperative strategies, despite this behaviour being in contrast to that prescribed by the stage game equilibrium. In particular, cooperative behaviour was more widespread when agent fitness was evaluated among other strategic agent in their community with respect to their overall utility rather than their immediate reward, and the adoption of alternative strategies was stochastic (*cf.* Section4.4).

The viability results are similar with the previous ones presented here; the intuition and conclusions drawn from the previous results do not change. Interestingly, however, we observe that the average number of household agents adopting a defective behaviour after the eruption is increased and exceeds those that adopt a cooperative one (Figure 5.10).[1]

This indicates that the eruption also had a strong impact on the social behaviour of the household agent communities. This observation is in line with the fact that conflict usually arises due to problems with the allocation of resources for rehabilitation after a disaster, given its impact on natural resources [40].

[1]We assume the same strategic actions for the agents as the ones presented in Section 4.2, cooperation (C), defection (D) and equivalent retaliation (TFT).

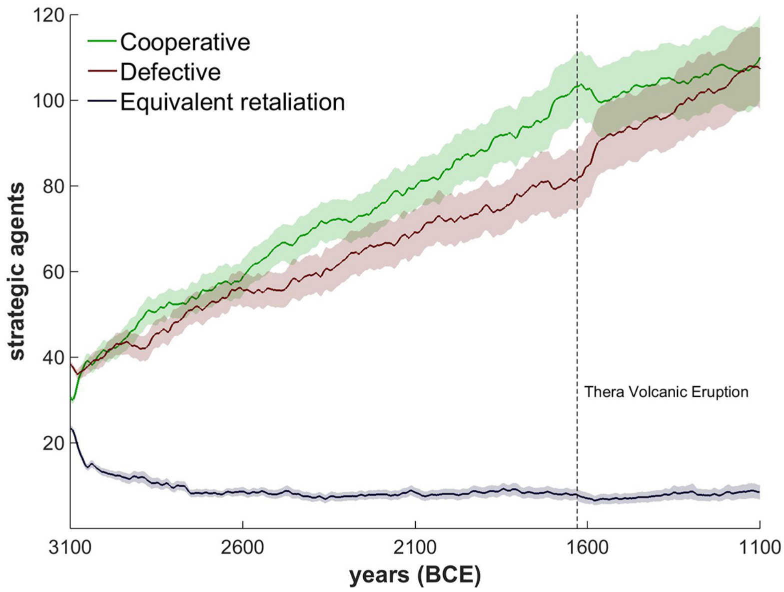


Figure 5.10: Strategic agent population over 2000 (yearly) time steps for the *default* case scenario, considering 15% mortality rate.

5.4 Conclusions

In this chapter, we attempted to deepen our understanding of the Bronze Age Minoan civilization's decline by incorporating natural disaster module in our ABM system for simulating various scenarios. Specifically, we explored whether the Minoan eruption of the Thera volcano was a catalyst, through its environmental and human impact, which triggered a disintegration process in early Minoan communities. Household agents were assumed to be located in the wider area of the *Malia* region at the island of Crete, employing different social organization paradigms. We tried to assess the imminent social crisis in terms of household and settlement sizes, migration behaviour, and evolution of agent strategic behaviour, before and after the eruption.

Simulation results over a number of different scenarios show higher non-cooperative household agent numbers after the eruption. This result potentially provides support to archaeological hypotheses of decentralization, which led to political fragmentation and internal conflict with increasing competition, largely related to the acquisition of resources [42]. Moreover, we observed a significant change in settlement distribution patterns, an effect of high mobility and crop loss rates, rendering a landscape with higher number of "small-size" settlements during the LM period. Archaeologists argue that the number of settlements or households, of ritual sites and of funerary sites that were abandoned during LM IA is considerable, however, they cannot yet distinguish archaeologically between a mature (*i.e.*, prior the eruption) and final (*i.e.*, contemporary to the eruption) abandonment [40]. In addition, in our simulations increased storage amounts were also observed after the eruption, suggesting collection of resources organized on a greater scale. Surprisingly, recent excavations have brought evidence pinpointing towards an increase in storage space in the mature LM IB phase, while the reduction in population size, change in the distribution of human groups, including their mobility patterns, and the conversion of food into direct and indirect storage, are all features evidenced during LM IB [42]. Overall, simulation results suggest that the Theran eruption led to a gradual breakdown of the pre-eruption Minoan socio-economic system.

Chapter 6

Simulating Trade across Agent Communities

In this chapter we put forward a novel agent-based trading module, for simulating the exchange and distribution of resources across settlements in past societies. The module is incorporated in our ABM system populated with autonomous, utility-maximizing agents corresponding to households; and can employ any spatial interaction model of choice. As such, it allows the study of the settlements' trading ability and power, given their geo-location and their position within the trading network, and the structural properties of the network itself. We use as a case study the Minoan society during the Bronze Age, in the wider area of *Knossos* at the island of Crete, Greece. We instantiate two well-known spatial interaction sub-models, *XTENT* and *Gravity*, and conduct a systematic evaluation of the dynamic trading network that is formed over time. Our simulations assess the sustainability of the artificial Minoan society in terms of population size, number and distribution of agent communities, with respect to the available archaeological data and spatial interaction model employed; and, further, evaluate the resulting trading network's structure (centrality, clustering, *etc.*) and how it affects inter-settlement organization, providing in the process insights and support for archaeological hypotheses on the settlement organization in place at the time.

Simulation results show that modeling a trading network that takes into account mainly the settlements' "importance" (*e.g.*, in terms of population size or lifetime) rather than solely the distance between settlement locations, can produce settlement patterns similar to the one that exist in archaeological record. However, this is most appropriate when the settlements' importance is known or can be derived based on archaeological evidence, thus allowing such a trading model to better capture the trend in settlement numbers that exist in the archaeological record. By contrast, when settlements' importance is not known, or cannot be properly modeled, then a trading network model should favour the distance between settlements rather than their importance.

Overall, the evolution of the values of the graph-theoretic indices characterizing our simulations' network, (*i.e.*, clustering coefficient, in-degree and out-degree centrality) indicate that the Minoan's trading network (at the modeling area) was affected by the Theran volcanic eruption. Specifically, it appears that the trading network in the Late Minoan (LM) period becomes clearly more dense, while it seems that there exist only a few "important centres" at the time, which is in line with the archaeological record. Moreover, it appears that the network's structure and interaction patterns are to an extent reversed after the Theran eruption, when compared to those in effect in earlier periods.

The main contributions of our work in this chapter can be summarized as follows, also illustrated in Figure 6.1 below:

- We provide a novel trading model that readily incorporates spatial interaction paradigms to simulate trade among self-organized communities of autonomous utility-based agents.
- We incorporate a natural disaster sub-model into the ABM, to provide insights on how a natural disaster scenario could have affected the trading network behaviour and further the agent communities organization structure.
- We utilize graph theory to analyze the trading network, and thus interpret simulation results in terms of the network's potential centralization, clustering behaviour

or potential settlement organization during the whole simulation period.

- Our systematic study of the dynamic trading network provides support to certain archaeological hypotheses related to the period and modeling area of study.

- We exploit simulation results to derive intuitions regarding the appropriateness of different spatial interaction models.

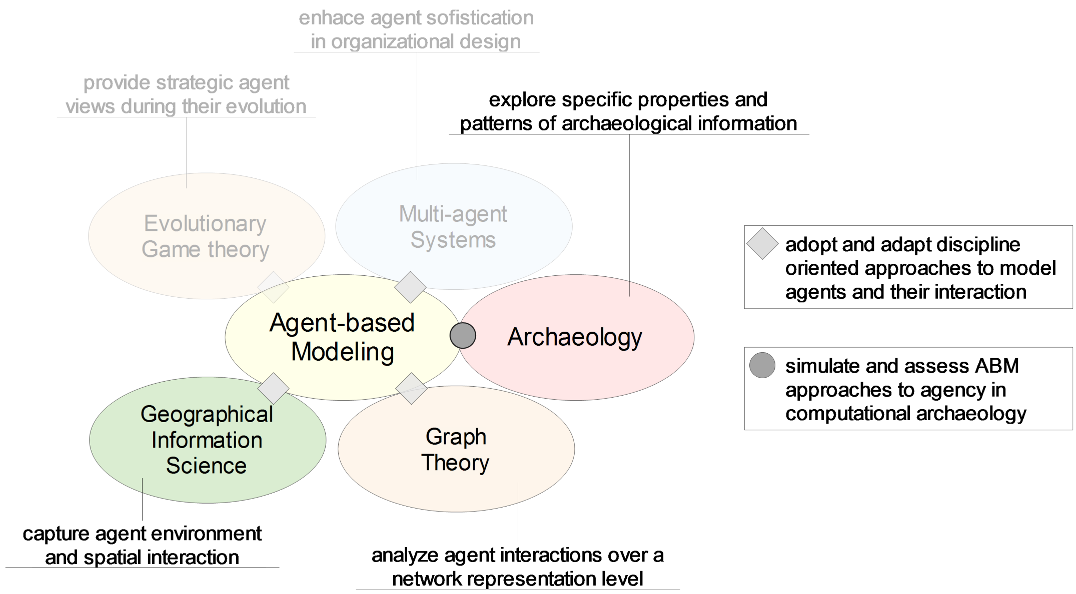


Figure 6.1: Overview of involved scientific fields and contributions in Chapter 6.

The remainder of this chapter is structured as follows. Section 6.1 provides a brief overview of formal techniques available for the study of trade in archaeology, and of existing examples of related archaeological ABMs in the literature. Section 6.2 presents the theoretical background of the modeling process that was followed for developing the trading network across settlements, based on both the XTENT and Gravity spatial interaction models. There, we also introduce several concepts from network and graph theory required for the analysis of the resulting trading network. Section 6.3 then presents our specific case study of early Minoan societies located at the wider central area of Knossos in the island of Crete. In addition, we record the empirical evaluation of the various trading models, in terms of potential settlement centralization and organization emerged during the Minoan period, by first detailing the simulation parameters for the various scenarios considered, and then analysing the obtained results. Finally, Section 6.5 concludes this work, and provides a brief discussion on simulation results.

6.1 Background

Certainly, in the absence of written records it is not easy to determine what were the mechanisms of trade, or what was the nature of the exchange relationship. However, several formal techniques are available for the study of trade, such as the development of a distribution map for finds or materials, within a specific geographic area [107]. Considering such distribution maps, pondered by fall-off analysis, the quantity of a traded material usually declines as the distance from the source increases.

For instance, let us consider a "down-the-line" trading system [107]. If one site, e.g. village, receives its supplies of a raw material down a linear trading network from its neighbour site up the line, it may retain a given proportion of the material for its own use, and trade the remainder to its neighbour site down the line. If each village does the same, an exponential fall-off curve will result, as illustrated in Figure 6.2. In some cases, however, there are regularities in the way in which the decrease occurs, and this pattern can inform us about the mechanism by which a material reached its destination. As an example, a different distribution system, through major and minor sites, would produce a different fall-off pattern, in particular, a multi-modal fall-off curve, since lower-order settlements tend to exchange with higher-order centres, even if the latter lies further from the source than an accessible lower-order settlement (Figure 6.2). We note at this point that in the rest of this paper we shall use the term ”settlement” to refer to any site category, such as village, town, or city.

Now, to the best of our knowledge, the only archaeology-related ABM that utilizes a spatial interaction model, is that of [54]. The ABM simulates movement of trav-

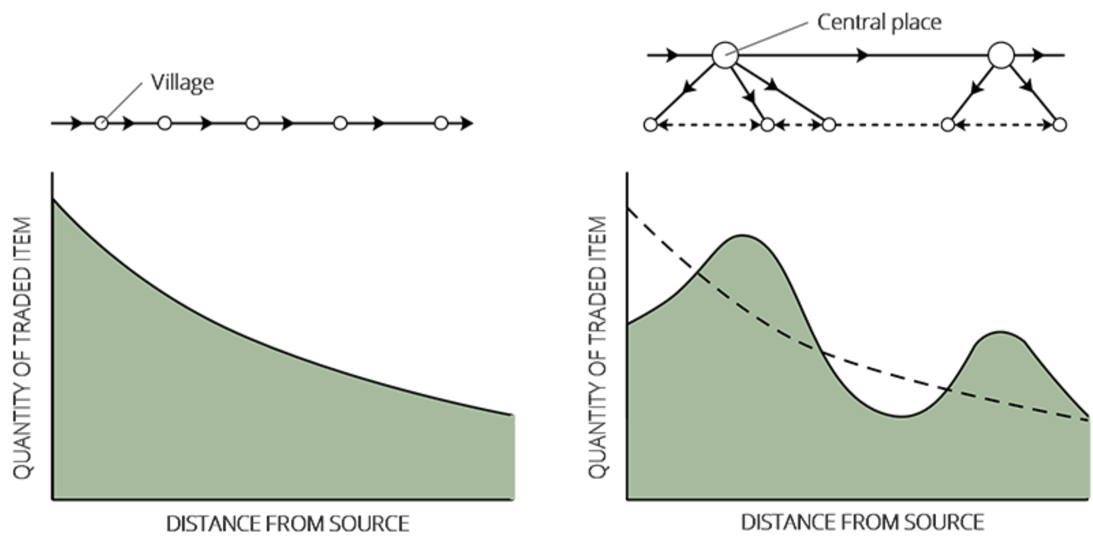


Figure 6.2: Relationship between settlement organization, type of exchange, and supply, for resources traded on land. *(Left)* Down-the-line exchange of village site. *(Right)* Exchange between lower-order with the higher-order sites. Adapted from [107].

ellers (agents) between settlement locations known through archaeological field survey in specific regions of Central Greece during the Geometric period and Central Italy during Protohistory. The author utilizes an entropy-maximizing model, that is, the Gravity spatial interaction model, in order to ultimately rank the settlements by the number of times they emerged as most "important" in the various metrics of the travellers network. Agents in the ABM are only able to travel to settlements around their neighbourhood and only to the most attractive site out of three potential destinations. Although the factual description of the ABM is missing, since the author argues that the mathematics in the ABM are not the most important consideration, but rather the description of how the agents interact, some indicative results are presented and discussed.[1]

[1] We could not conduct further analysis or validation of the specific ABM, since the URL of the ABM source code no longer exists.

6.2 Modeling the Trading Process

A possible solution to conceptualize exchange and distribution of resources (flows) between settlements, relies on using a *spatial interaction model [107, 110]*. The basic assumption regarding spatial interaction models is that flows are a function of the attributes W_i of the origin location i, and the attributes W_j of the destination location j and the "friction" of distance $D_{i,j}$ between the concerned origin and destination locations. The general formulation of the spatial interaction model is as follows [110]:

$$I_{i,j} = f(W_i, W_j, D_{i,j}) \tag{6.1}$$

In our work here, $I_{i,j}$ represents a measure of "attractiveness" corresponding to the probability of trade between settlements i and j. $D_{i,j}$ is the distance between the settlement locations.[2] Variables W_i or W_j are used to express a measure of "importance" for settlement i and j, respectively. Attributes often used to express such variables are socio-economic in nature, such as population or gross domestic product in modern societies.

Since we are calculating settlements' interaction probability at any given time step t during the simulation, we consider the following attributes:

- $P_{j,t}$, defined as the ratio of the population (inhabitants) of settlement j with respect to the total population at time t, and
- $K_{j,t}$, defined as the ratio of the number of time steps that settlement j has existed so far up to t.

Then, at any given time step t, we define the importance $W_{j,t}$ of a settlement location j as follows:

[2] The distance factor $D_{i,j}$ is measured as the Euclidean (linear) distance for simplicity. This distance can be alternatively measured as the Least Cost Path between two settlement locations, considering slope and elevation as cost surfaces, however, with significantly higher computational cost.

$$W_{j,t} = \sqrt{P_{j,t}} \cdot \sqrt{K_{j,t}} \tag{6.2}$$

For example, if at time step t = 1000, S_i settlements exist in the ABM environmental area, where $i = 1, 2$ and the total population is 8000 inhabitants, assuming that S_1 has a population of 2880 inhabitants and a lifetime of 810 years and S_2 has a population of 5120 inhabitants and a lifetime of 360 years up to current (annual) time step t, then $W_{i,t}$ is calculated as follows:

$$W_{1,1000} = \sqrt{P_{1,1000}} \cdot \sqrt{K_{1,1000}} = \sqrt{\frac{2880}{8000}} \cdot \sqrt{\frac{810}{1000}} = 0.6 \cdot 0.9 = 0.54$$

$$W_{2,1000} = \sqrt{P_{2,1000}} \cdot \sqrt{K_{2,1000}} = \sqrt{\frac{5120}{8000}} \cdot \sqrt{\frac{360}{1000}} = 0.8 \cdot 0.6 = 0.48$$

Thus, settlement S_1 has a higher weight (importance) than settlement S_2, even though S_2 has an almost double population size than S_1, due to the higher lifetime of S_1 during the simulation.

Now, past societies of the first farmers in different parts of the world, may be generally described as independent sedentary and relatively egalitarian communities without any strongly centralized organization [107]. Following the development of farming, in many cases, the farming economy underwent a process of intensification, associated with developing exchange. Given this, we make the following assumption: at any given time step t, each (household) agent within a settlement i is socially contracted as a community member to give away a portion of its stored surplus ps (*e.g.*, 20% or 80%) to be communally pooled as the corresponding settlement trading resources $N_{i,t}$ and be traded away by the settlement later on. We note that the percentage of surplus resources that an agent is able to give away is user-defined in our ABM.

For instance, if at time t = 1400, settlement S_{53} has $i = \{1, 2, 3\}$ household agents, where each agent has st_i surplus resources in its storage, *e.g.*, st_1 = 100, st_2 = 200, st_3

= 50, while the user-defined percentage of stored surplus to be given away is ps = 20%, then the settlement's overall trading resources unit $N_{53,1400}$ are calculated as follows:

$$N_{53,1400} = ps \cdot \sum_{i=1}^{3} st_i = 0.2 \cdot (100 + 200 + 50) = 70$$

Then, since the level of interaction or "attractiveness" I_{ij} of settlement i corresponds to the probability of trading with any other settlement j, settlement i can ultimately trade and exchange resources $E_{ij,t}$ with settlement j at time step t, by distributing its trading resources $N_{i,t}$ based on its interaction probability $I_{ij,t}$, as follows:

$$E_{i,j,t} = \frac{I_{i,j,t} \cdot N_{i,t}}{\sum_{j=1}^{n} I_{i,j,t}} \tag{6.3}$$

To give some intuition on the calculation of $E_{i,j,t}$ let us provide another example; however, in order to not overload notation, we are dropping the t index, when this is not required. Thus, if we consider a set of potentially interacting settlements S_i where $i = \{1, 2, 3, 4, 5\}$ and $I_{i,j}$ is provided by some spatial interaction model, *e.g.*, the XTENT or Gravity used in this work, so that $I_{1,2} = 0.2$, $I_{1,3} = 0.6$, $I_{1,4} = 0.8$, $I_{1,5} = 0.4$ then settlement S_1 will distribute a portion of its trading resources, *e.g.*, N_1 = 200 (in kg) to settlement S_2, as follows:

$$E_{1,2} = \frac{I_{1,2} \cdot N_1}{\sum_{j=1}^{5} I_{1,j}} = \frac{0.2 \cdot 200}{0.2 + 0.6 + 0.8 + 0.4} = 20$$

As such, S_1 will give away 10% of its overall trading resources to settlement S_2, 30% to settlement S_3, 40% to settlement S_4 and 20% to settlement S_5—in the event that trade occurs with the corresponding probabilities. Similarly, when the trading process is over, settlement i will proportionally distribute the "public good" payoff among its household agents, based on their number of inhabitants. Let us now elaborate on the *XTENT* and *Gravity* spatial interaction models, immediately below.

6.2.1 The XTENT model

The XTENT model asserts some relationship of settlement size and distance, whereby the larger *dominates* the smaller if the distance between them is sufficiently small, whereas the smaller retains autonomy if that distance is large enough [109]. Thus, it assumes that a large centre will dominate a small one if they are close together; in political terms the smaller site has no independent or autonomous existence. This approach overcomes the limitation of the *Thiessen polygons* method, where territories are assigned irrespective of the size of the settlement, and where there are no dominant or subordinate settlements, allowing a simple approximation of the political reality and a hypothetical political map to be constructed [107].

In our ABM, the "attractiveness" determining the level of trading interaction of settlement i (origin location) with settlement j (destination location) that relies on the XTENT formula, is proportional to the importance of the destination location and declines linearly with their distance, as follows:

$$I_{i,j} = W_j^{\beta} - m \cdot D_{i,j} \tag{6.4}$$

where β and m are constants used to adjust the required level of the effect that the importance W_j of settlement j and the distance $D_{i,j}$ have on the overall "attraction" between settlements i and j, respectively. Of course, one has to experiment with specific values for β and m to reflect the required attraction between settlements i and j. Moreover, in order to turn $I_{i,j}$into a meaningful trading probability between settlements i and j we choose to scale its value to [0;1] (min-max normalization).

Given the $I_{i,j}$'s, we are able to provide visualization intuitions about settlement territories by coloring each "cell" in the modeling area with the same color of the settlement which is mostly attracted to (in this way the territory of some smaller settlement is simply absorbed to that of its adjacent larger one). For instance, if we assume thirty (30) different settlements as destination locations j and that origin locations i are all other landscape cells in our modeling area in this paper, considering $\beta = 1.5$ and $m = 0.005$, then the XTENT model provides a landscape partitioning (territories) for the trading process as the one illustrated in Figure 6.3.

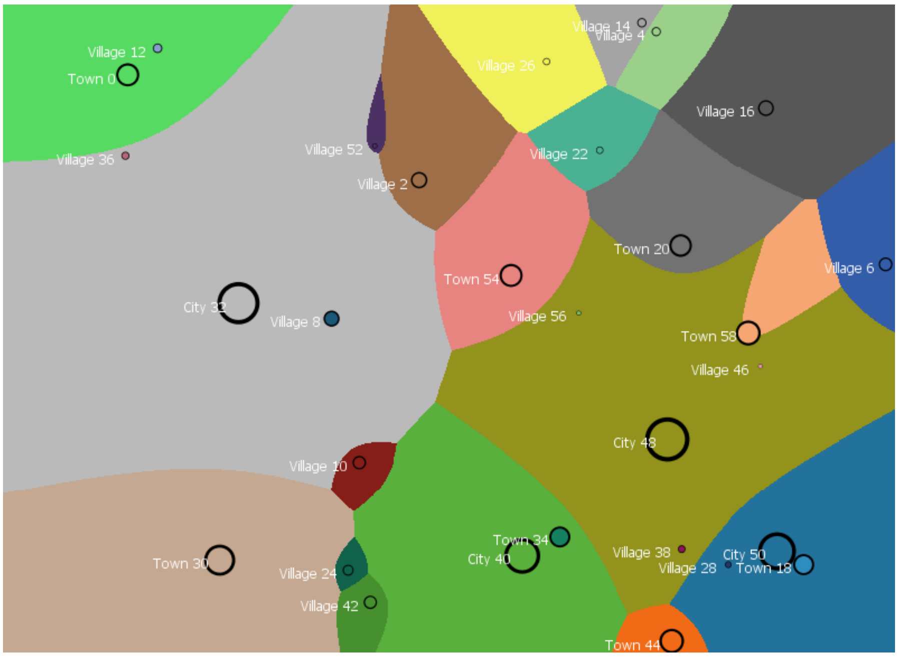


Figure 6.3: Visualization of "territories" of 30 different settlements (of type village, town or city) within the modeling area, considering the XTENT spatial interaction model, considering $\beta = 1.5$ and $m = 0.005$.

In the example of Figure 6.3, each settlement is depicted with a unique coloured circle, where its size represent its importance with respect to its type (village, town or city in this example), while its territory (landscape partitioning) is depicted with the same color. In particular, settlement 8 (of type village), located near the centre of the modeling area, will most probably trade with settlement 32 (city) or even settlement 10 (village), since it is attracted to settlements that are relatively close in range, undervaluing the importance of settlements that are further away.

6.2.2 The Gravity model

The Gravity model is the most common formulation of the spatial interaction method [72, 69]. It is named as such because it uses a similar formulation as the Newton's law of gravity. The "attractiveness" between the locations of origin (of trade) i and destination j that relies on the Gravity model is proportional to importance, and inversely proportional to their respective distance [110]:

$$I_{ij} = W_j / D_{ij}^{\lambda} \tag{6.5}$$

In the above formula we do not take into account the importance of the origin settlement W_i, since we need to model the trading probability and the "attraction" of the destination settlement j, same as in the XTENT formula, thus the "attractiveness" between settlements i and j is not reciprocal. One would of course need to experiment with λ in order to efficiently reflect the required (growing) effect that distance have to the trading probability between settlements i and j. In our simulations experiments and same as with the XTENT model, $I_{i,j}$ is also scaled to [0;1] (min-max normalization).

Let as also provide visualization intuitions about settlement territories relaying on the Gravity model, by assuming the same thirty (30) different settlements as in the previous example (*cf.* Figure 6.3) as destination locations, and origin locations to be any landscape cell in the modeling area, considering $\lambda = 0.2$. Now, settlement 8 (village) will most probably trade with settlement 32 (city) or even settlement 30 (town), since it is attracted with settlements of high importance, that is of type city or town, despite its distance from them.

6.2.3 Discussion on spatial interaction models used

In the simulation scenarios described later on, we consider two different views on the trading probability between settlements; one favouring the distance between settlements

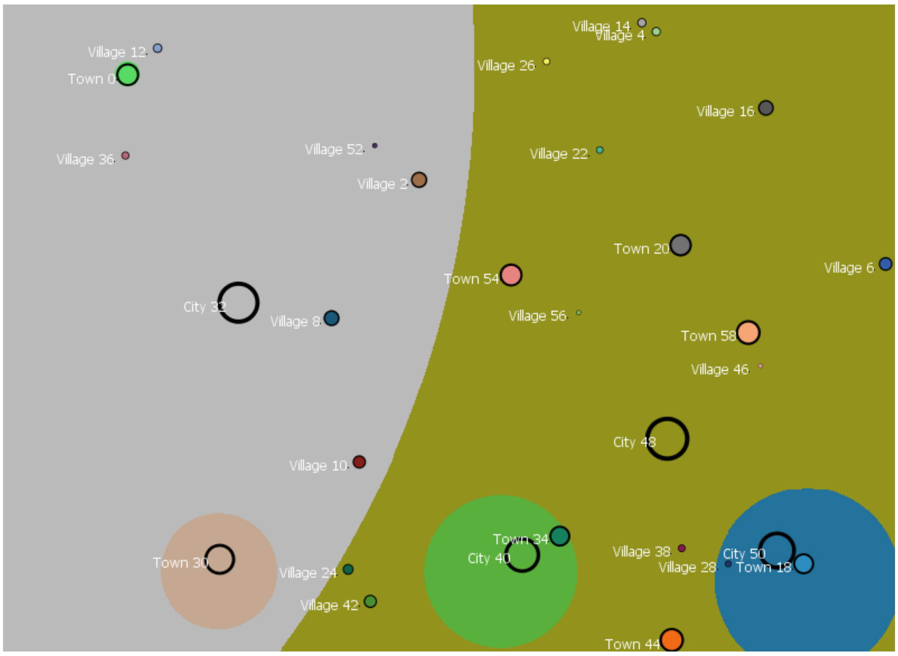


Figure 6.4: Visualization of "territories" of 30 different settlements (of type village, town, city) within the modeling area, considering the Gravity spatial model, considering $\lambda = 0.2$.

rather than its importance, relying on the XTENT model with $\beta = 1.5$ and $m = 0.005$ (Equation 6.4), and another favouring the importance of settlement locations rather than the distance between them, enabled by the Gravity model with $\lambda = 0.2$ (Equation 6.5). We will observe these models' effect on settlement organization and distribution patterns in our simulation results.

The aim of assigning the specific values of β and m for the XTENT model, and of λ for the Gravity model, is to adequately model the required trade-off between settlements distance and importance for the specific case study's geographic area described later on (maximum distance of about 40 km). To provide an intuition on the two different views on the trading probability between settlements, let us assume that the probability distribution of "importance" for a potential destination settlement is as illustrated in Figure 6.5 (the blue dashed sinusoidal curve). The corresponding probability distribution of interaction of an origin settlement with the respective destination location is then depicted with the red and yellow curve, considering the XTENT and Gravity models, respectively. As shown in Figure 6.5, the distance between the origin and destination settlements has a greater role when the XTENT method is employed, while it has a lesser impact when the Gravity model is in use.

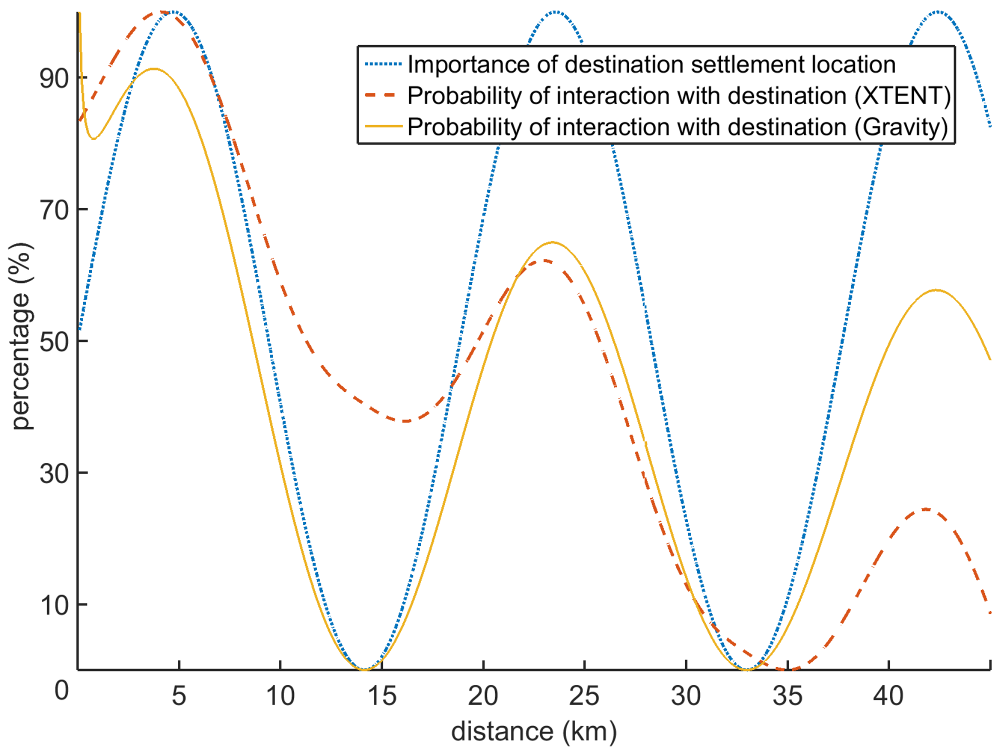


Figure 6.5: Probability distribution of importance of a potential destination settlement location and the corresponding distribution probability of interaction of an origin settlement location, considering the XTENT model with $\beta = 1.5$, $m = 0.005$ and the Gravity model with $\lambda = 0.2$.

6.2.4 Graph theory for trading network analysis

In our ABM, settlements interact with several other settlements, formulating a different trading network at every given time step during the simulation, based on the enabled trading scheme (XTENT or Gravity model). What we need to explore in such a *dynamic* trading network of settlements, is whether and to what degree some settlements are more important or central than others, based on their trading interactions; and whether settlements tend to create groups characterised by a relatively high density of trading interactions. Thus, in order to better understand and provide insights on the consequence of patterns of interaction between settlements, we adopt in our work some of the main approaches that *network and graph theory* has developed. We describe these below.

To begin with, a trading network can naturally be represented by a *graph*. A graph consists of a set of *points* and a set of *edges* or ties connecting pairs of points. In our case, each settlement in the trading network corresponds to a point in the graph and each trading interaction corresponds to an edge that connects a pair of settlement locations.

A fundamental measurement concept for the analysis of network graphs is *centrality*, that can highlight important information about the network organization and its structure [49]. Centrality index describe point locations in terms of how close they are to the "centre" of the network activity. Thus, settlements who have more interaction ties (edges) to other settlements may be in advantaged positions. Because they have many interaction ties, they may have access to more of the exchanged resources over the network as a whole, and hence are less dependent on other settlements [64].

Whenever two settlements trade, they are directly connected by an edge, and thus, they are adjacent. The number of other settlements to which a given settlement is adjacent is called the *degree* of that settlement. A simple and effective measure of a settlement's centrality is its *degree*. Since resources can be exchanged in a single edge direction towards another settlement, the temporal trading network of the ABM is represented as a "directed" graph and it is important to distinguish centrality based on *in-degree*, from centrality based on *out-degree*. If settlements receive many interaction ties, they can be described as *prominent*, or having high *prestige*, since many other settlements seek to direct resources to them, and this may indicate their *importance* [64]. Settlements with high out-degree centrality are able to distribute resources to many other settlements, or make many other settlements aware of their resource exchange potential, thus being more *influential* than settlements with low out-degree centrality; although it might matter to which settlement they are distributing resources, this measure does not take that into account [64].

Let us now assume that a potential trading network is formulated with n number of settlements S_j (network nodes), at a specific time step during the simulation in our ABM. This snapshot of the trading network can be represented as a directed graph, where numerous trading interactions occur between settlements. The *in-degree* or *out-degree* centrality index $C_D(S_j)$ is the number of incoming or outgoing trading edges, respectively, for a settlement S_j [49]:

$$C_D(S_j) = \sum_{i=1}^{n} tr(S_i, S_j) \tag{6.6}$$

where, $tr(S_i, S_j) = 1$ if and only if S_i and S_j interact (trade resources) and thus, connected by a tie or edge; and $tr(S_i, S_j) = 0$, otherwise. The magnitude of $C_D(S_j)$ for a settlement j partly depends of the size of the trading network on which it is calculated. However, since our trading network is *dynamic* and constantly changes during its evolution, it is desirable to have a measure that is independent of network size. Thus, we calculate the *relative degree centrality* ${C_D}'(S_j)$ for a settlement j, which is defined as:

$${C_D}'(S_j) = \frac{C_D(S_j)}{n-1} \tag{6.7}$$

The effect of network size has been removed by normalizing with $\max C_D(S_j) = n-1$, since any given settlement S_j can at most be adjacent to $n-1$ other settlements in the trading network graph. Overall, the degree of a settlement point can be viewed as an index of its potential *trading activity*.

Another view of settlement point centrality, within a "directed" network graph, is based on the frequency with which a settlement S_k falls between pairs of other settlements on the shortest or "geodesic" paths connecting them, defined as the *relative betweenness* centrality index [136]:

$$C_B{}'(S_k) = \frac{\sum_i^n \sum_j^n b_{ij}(S_k)}{(n_I-1)(n_O-1)-(n_S-1)}, \quad b_{ij}(S_k) = \frac{g_{ij}(S_k)}{g_{ij}}, \quad i \neq j \neq k \tag{6.8}$$

where g_{ij} is the number of geodesics linking S_i and S_j, $g_{ij}(S_k)$ is the number of geodesics linking S_i and S_j that contain S_k and, b_{ij} is the probability that point S_k falls on a randomly selected geodesic linking S_i with S_j. Similarly to the relative degree centrality $C_D{}'(S_k)$ of a settlement S_k, the measure is also independent of the dynamic trading network size, since it is normalized by the maximum betweenness centrality of a settlement S_k, that is $(n_I-1)(n_O-1)-(n_S-1)$, where n_O is the number of settlements with outgoing edges, n_I the number of settlements with incoming trading links and n_S the number of settlements with reciprocated edges [136]. A settlement point in such a position of high relative betweenness centrality can influence other nearby settlements by holding resources in exchange, exhibiting a potential for control of their distribution. It is this potential for control that defines the centrality of these settlements.

Now, when centrality is applied to the whole trading network graph, such a measure should index the degree to which the centrality of the most central settlement exceeds the centrality of all other settlements, and it is expressed as a ratio of that excess to its maximum possible value for the network graph containing the observed number of settlement points [49]. Thus, the relative degree graph centrality index varies between 0 and 1, and is defined as follows:

$$C_D{}' = \frac{\sum_{i=1}^n [C_D{}'(S^*) - C_D{}'(S_i)]}{\max \sum_{i=1}^n [C_D{}'(S^*) - C_D{}'(S_i)]} \tag{6.9}$$

where n is the number of settlement points, $C_D{}'(S_i)$ is the relative degree centrality defined above for settlement S_i, and $C_D{}'(S^*)$ is the largest value of $C_D{}'(S_i)$ for any settlement in the trading network graph. The maximum possible sum of differences in settlement relative degree centrality, $\max \sum_{i=1}^n [C_D{}'(S^*) - C_D{}'(S_i)]$, is reduced to $\frac{n^2-3n+2}{n-1} = n-2$ for the relative degree graph centrality index [49].

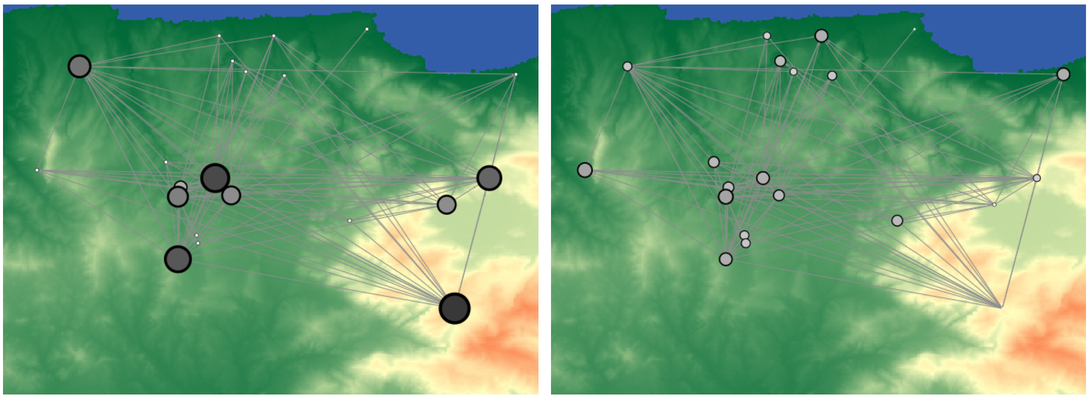
Similarly, the relative betweenness graph centrality index varies between 0 and 1, and is defined as follows:

$$C_B{}' = \frac{\sum_{i=1}^{n}[C_B{}'(S^*) - C_B{}'(S_i)]}{\max\sum_{i=1}^{n}[C_B{}'(S^*) - C_B{}'(S_i)]} \tag{6.10}$$

where n is the number of settlement points, $C_B{}'(S_i)$ is the relative betweenness centrality for settlement S_i and $C_B{}'(S^*)$ is the largest value of $C_B{}'(S_i)$ for any settlement in the trading network graph. The maximum possible sum of differences in settlement relative betweenness centrality, that is, $\max\sum_{i=1}^{n}[C_B{}'(S^*)-C_B{}'(S_i)]$ is reduced to $n-1$ for the relative degree graph centrality index [136].

Then, high relative in-degree or out-degree graph centrality means that there are few settlements of high importance, or highly influential settlements respectively, in the trading network (and thus the most prominent or influential settlement in the network really "stands out", making the value of the numerator in Equation 6.9 go up). On the other hand, low relative in-degree or out-degree graph centrality means that there are many settlements with a similar level of influence or importance. Accordingly, high relative betweenness graph centrality means that there are few settlements with high potential for control in the trading network, while low relative betweenness graph centrality means that there are many settlements that exhibit a similar potential for control in the network.

To provide visualization intuitions on the relative network graph centrality [49] we present a snapshot of the trading network developed during a random simulation run. In the example of Figure 6.6, each settlement node in the trading network is depicted with a circle, where its size and color represents its relative centrality value [0; 1], with white color corresponding to the minimum value (0) and black color corresponding to the maximum centrality value (1). Figure 6.6a illustrates a trading network of settlements with high relative graph centrality, while the one in Figure 6.6b shows the same network but with low relative graph centrality.



(a) (b)

Figure 6.6: (*a*) High and (*b*) low relative graph centrality indices of a trading network of settlement nodes, represented as circles and trading connections as links between them. Settlement nodes size and color represent their centrality value, from minimum (white) to maximum (black).

Besides the above relative graph centrality indices that will be used to evaluate the settlement trading network structural evolution, the degree to which settlements in the network graph tend to cluster together is also examined in our work, by calculating the network's average *clustering coefficient* [133]:

$$\tilde{C} = \frac{1}{n}\sum_{i=1}^{n} C_i \tag{6.11}$$

where n is the number of settlements in the trading network graph and C_i is the number of ties between settlement S_i's neighbours, divided by the total number of possible trading edges between its neighbours. C_i represents how connected settlement S_i neighbours' are. Thus, the network's average clustering coefficient $\tilde{C}$ measures the degree to which settlements tend to cluster together within the trading network.

6.3 Case study: the Minoan society in Central Crete

There is not 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. The sophistication of the Minoan culture and its trading capacity is evidenced by the presence of writing (mostly found on various types of administrative clay tablets). The content of the Minoan texts that have been unearthed is predominantly economic (inventories of goods or resources) and religious. Scholars argue that even if relations among (and possibly within) the various towns and cities continued to be contentious and competitive, a common architectural language was beginning to emerge [93]. This new architectural language marks the beginning of a specifically Minoan identity, which defines a clear indication that each household was not a self-sufficient, totally independent economic unit, but that it was involved in *exchange*. Moreover, for the later Neolithic and Early Bronze Age, stylistic and petrographic analyses suggest a low-volume circulation of ceramic vessels, compatible with “gift exchange” economies, over short and long distances between different communities within and occasionally beyond the island [126]. This evidence allows us to conceivably model such relations as *resource exchanges*.

We note, however, that we do not intend to generally reduce human relations to *exchange*, as if human ties to society can be imagined in the same terms as a business deal [53]. Nevertheless, even Aristotle was speculating along similar lines in his treatise on *Politics*. At first, he suggested, families or households must have produced everything they needed for themselves. Gradually, some would presumably have specialized, some growing corn, others making wine, *swapping or trading* one for the other [8, 53]. Therefore, although we do not have a clear picture of how human relations (interactions) were actually formed in prehistoric time periods, we need to have a conceivable conceptual model in mind, and that is done with the simplest possible way: to model *trading* among them as an *exchange of resources*—thus, giving us the ability to encode the conceptual model as an ABM encompassing various spatial interaction models for the resource exchange process, enabling us to explore a range of the its corresponding trading network structure in turn.

In addition, archaeologists argue that Minoan palaces are considered to be one of the central factors in bringing about social transformation in the Minoan civilization [19]. In their view, the construction of Minoan palaces came about through a socio-political “quantum leap” from Chiefdom to State. This leap involved also the introduction of writing, the first centrally organized religion (the peak sanctuaries), and the development of social hierarchy and interacting social networks. Moreover, the size of such “grand” public structures at several sites requires both a considerable population and a social cohesion, and it can reasonably be assumed that there were different levels of importance, *i.e.* a hierarchy of sites [39].

Starting from the above archaeological information about the Minoan society subsistence and assumptions during their evolution, and associated archaeological data, we shall try to assess the resulting trading network structure over time and its effect on the Minoan society social organization at the community level, providing insights on settlement clustering and organization during the Bronze Age.

6.3.1 Model environment

The environment is considered to be the geographic area of the wider region of Knossos, located approximately in central part of the island of Crete. As a result, known habitation sites of the Minoan period where identified, categorized and geolocalized, acquired by the “Digital Crete” project.[3] Agents are located within a 40×30 km area with one (1) hectare cell size for the grid space. Moreover, the environment has also associated data layers representing topographical aspects of the model landscape, such as elevation, slope and aquifer locations, contributing indirectly in agent’s decision-making process, like where to settle and/or cultivate (Figure 6.7).

[3] See http://digitalcrete.ims.forth.gr

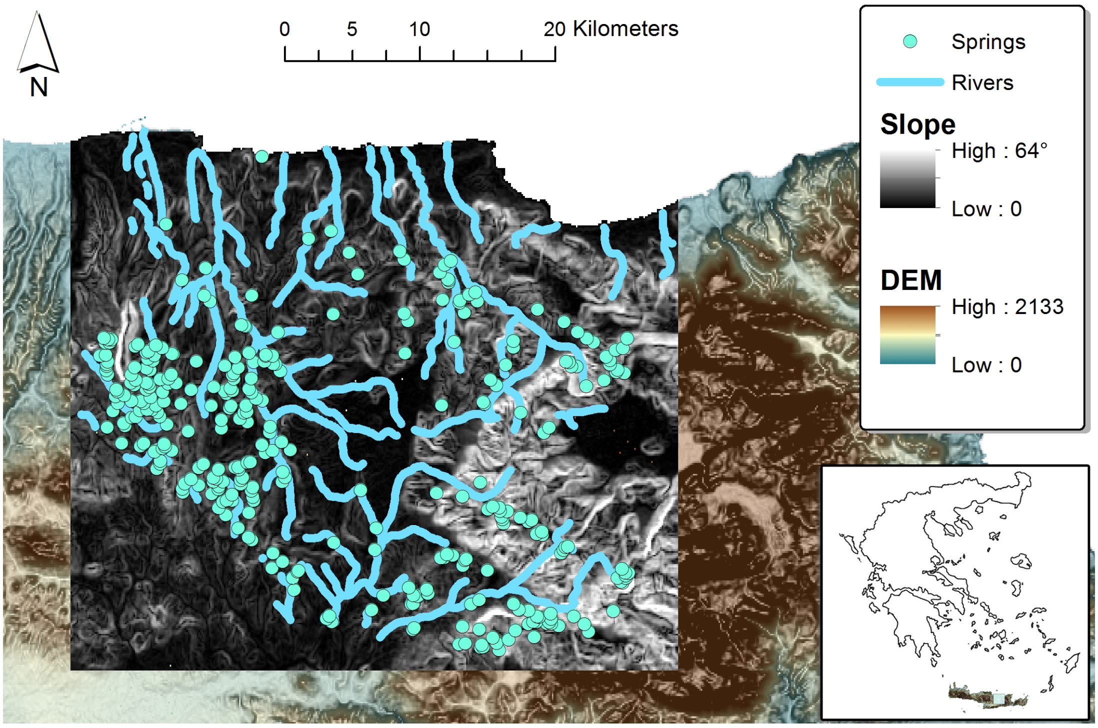


Figure 6.7: Modeling area and its topographical features at central Crete, Greece

6.3.2 Model instantiation

The estimated per hectare population for an agricultural Minoan settlement during the modeled era ranges from 100 up to 400 [71]. In our simulation experiments below, we assume a density coefficient of 250 people per hectare, that is, the maximum number of inhabitants per grid cell [39]. Moreover, the number of household inhabitants in a given settlement cell is initialized to a random number between 1 and 10. As a consequence, the maximum number of household agents per settlement's cell is 25, *i.e.*, 250 divided by the maximum number of inhabitants per household, that is 10. Household and settlements number and location are initialized based on archaeological record, *i.e.*, the number of settlements per scenario is set to 21, which are located at known habitation site locations.

Initial cell resources at a given simulation run are based on archaeological estimates on production yield per hectare (ha) pondered by the agricultural regime employed by the agents. As already noted, agents cultivation systems, can be either "intensive", producing 1500kg/ha or "extensive", leading to a production of 1000kg/ha on an annual basis (*cf.* Section 3.1.4). In our simulations below, we assume that household agents employ an intensive agricultural practice.

Agent migration radius, that is, the distance that a household agent can migrate to in one time step is set to the full environmental area ($\approx$ 40 km). An agent may migrate only to a cell where known habitation sites exist, based on the archaeological survey conducted in the specific geographic area. However, we assume a resettlement cost rc for an agent i, which intuitively reflects the decay of potential resources at destination location with increasing distance:

$$rc_i = 1 - e^{-0.005 \cdot \delta} \tag{6.12}$$

where δ is the distance (in km) of the agent to the respective migrating settlement location. The *rate* parameter of C function above is defined as 0.005 in order to achieve a relatively gradual decay of destination resources for an agent, *i.e.*, model a resettlement cost of about 20% of agent resources at 40km away.

As a final note, we consider a dynamic population growth, based on the amount of resources consumed by a household agent during the year. We consider a population growth rate of about 0.1%, when households consume adequate resources, same as in the simulations of previous chapters (*cf.* Section 3.1.3).

6.4 Simulation Scenarios and Results

We simulate trading across settlements of household agents that employ a "self-organization" social behaviour, as described in Section 3.2. Various scenarios were taken into account for the experimental setup, with different parameterization. Specifically, the main simulation scenarios are for our:

- two spatial interaction models, the XTENT and Gravity ones, and
- two different ways to characterize the importance of settlements, one based on Equation 6.2, and one based solely on available archaeological data ("site category bias" below)

We note that the natural disaster module is also enabled in our simulations, in an attempt to provide insights to whether the effects of the volcanic eruption of Thera (Santorini) affected the trading network behaviour (*cf.* Section 5.2. However, human impact, immediately after the Theran volcanic eruption, is assumed to achieve a mortality rate of 15% at the whole environmental area, due to one or more earthquakes that the eruption was preceded by (and probably even triggered by) and also due to large amounts of ash and pumice that were emitted. Thus, at the time step of the catastrophic event, each inhabitant in our modeling area has a 15% probability of dying. This is in contrast to the simulation scenarios considered in Chapter 5, where such a mortality rate was assumed only at the tsunami affected areas, linearly decreasing with distance to coastline.

Simulation results are averages for each time step over 30 simulation runs across a period of 2,000 years (*cf.* Table A.1 in Appendix A, for the conventional chronology dates (BCE) of the Minoan period used in our ABM simulation scenarios). Moreover, in all figures below, we depict shaded areas that correspond to 95% confidence intervals around lines corresponding to agent or network characteristics. In order to assist the reader, in all figures the legends are also ranked in accordance to the relative performance of the corresponding agent or trading network behavioural characteristic.

In terms of simulation time, the process can be quite expensive, since a single run (composed of 2,000 yearly time steps) takes approximately 24 hours on a single core 2.6 GHz computer. However, by utilizing the Grid computer of the Technical University of Crete (TUC), all the above 120 simulation runs were executed on thirty (30) dual-core

(2.6GHz) nodes (with 4GB ram each) in just two (2) days (this would have required otherwise four (4) months on a single-core computer).

We now proceed to discuss our findings regarding the trading network analysis performed on our area and era of interest, based on the spatial interaction models enabled and the available archaeological data.

6.4.1 Civilization sustainability and trading network evolution

We begin with presenting our findings regarding the effect of the different spatial interaction models on household agent population, settlements number, and their size. Simulation results are presented in Figure 6.8 for both the XTENT and Gravity models, considering a low percentage of stored surplus trading scheme, *i.e.* $ps = 20\%$, while agents in the model can settle or migrate only to known archaeological site locations at any specific time step. The 20% ps value is in our view a realistic assumption for the age and subsistence regimes studied, given that no sea trade is modeled in this work.

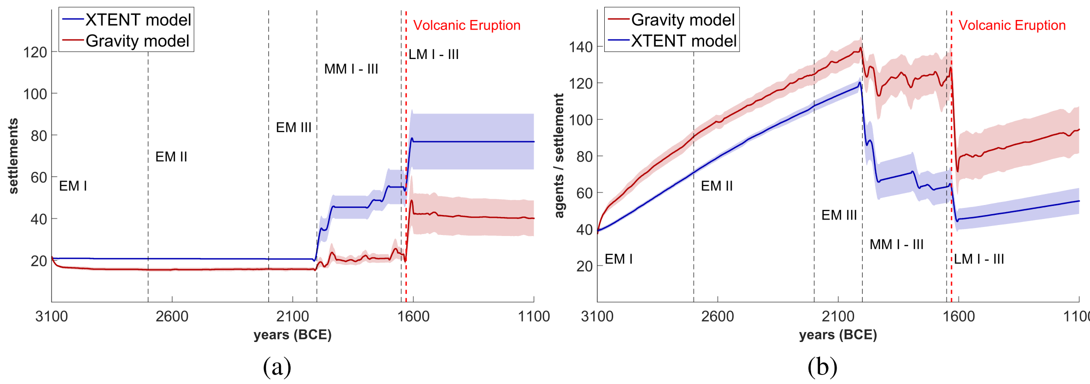


Figure 6.8: (*a*) Number of settlements and (*b*) settlements size over 2,000 yearly time steps (Minoan period), considering the XTENT and Gravity spatial interaction models.

When the XTENT spatial interaction model is used, we observe that the number of settlements remains almost constant until the end of the Early Minoan (EM) period, and then gradually increases over time, especially during the Middle Minoan (MM) period and even more after the volcanic eruption and Late Minoan I (LM I) period (Figure 6.8a). The number of agents (households) per settlement also appears to increase until the end of the EM period, and then gradually drops in the MM period. Immediately after the volcanic eruption, settlement sizes abruptly drop for a few decades, and start again to gradually increase during LM II and LM III periods (Figure 6.8b).

Then, when the Gravity model is employed for the trading process across settlements, we observe a similar behaviour with that of XTENT for settlement numbers and sizes, although the number of settlements is slightly lower than the XTENT model during the EM period, and then slowly increases over time, until the end of the MM period (Figure 6.8a). For both spatial interaction models, however, we observe an increase on settlements number and a gradual decline in settlement sizes during the MM period, due to the availability of a lot more known site locations for migration (*cf.* Figure A.1 in Appendix A). We also observe a relatively constant number of settlements after the volcanic eruption until the end of the LM period, with the XTENT model having higher numbers at about 80 settlements and the Gravity model at about 40 settlements on average. On the other hand, the number of agents per settlement is slowly increasing after the volcanic eruption until the end of the LM period, with the Gravity model achieving higher numbers of household agents on average than the XTENT model (Figure 6.8b).

Overall, a higher number of settlements is observed after the EM period, with an in-parallel decline on the number of households (agents) per settlement. The increasing trend of settlement numbers is in line with the archaeological record, at least until the LM I period, when actual settlement numbers abruptly decline until the beginning of the LM II period (see Figure A.1 in Appendix A), and then settlement numbers start to increase again until the LM III period.

We also report that the overall household agent population is constantly increasing at a dynamic population growth rate from about 820 initial agents to about 3450 and 2950 agents for the XTENT and Gravity spatial interaction models, respectively, with only an abrupt and short decline immediately after the volcanic eruption (Figure 6.9a). Furthermore, the stored surplus of agents is gradually decreasing during the whole simulation period, from about one ton to one half of a ton per household for both the XTENT and Gravity spatial interaction models, with only an abrupt increase immediately after the volcanic eruption of Thera and then again gradually decreasing until the end of the LM period (Figure 6.9b). This "shock" on the average storage of households immediately after the volcanic eruption, seems to ultimately affect the settlement trading network, since changes in clustering and centralization rates are observed during the LM period, as it will be explained later on.

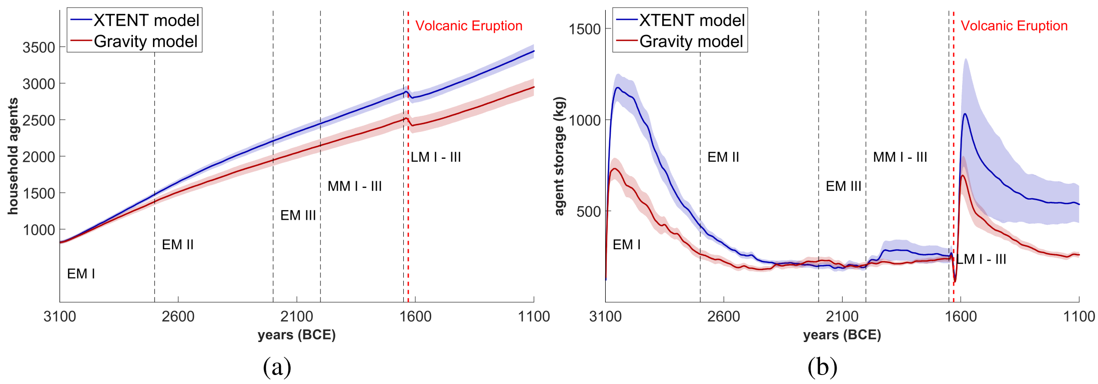


Figure 6.9: (*a*) Population and (*b*) average storage of household agents over 2,000 yearly time steps (Minoan period), considering the XTENT and Gravity spatial interaction models.

Let us now proceed on the study of the structural behaviour of our settlement trading network. In Figure 6.10 we present the average relative in-degree and out-degree network graph centralities during the 2,000 years simulation period. When the XTENT model is employed, the relative in-degree graph centrality gradually drops from about 25% to 20% until the end of the EM period (see Figure 6.10a) while the relative out-degree graph centrality gradually increases from about 20% up to 55% in the same time period (see Figure 6.10b); thereafter the relative out-degree graph centrality gradually declines to about 40% until the end of the MM period, abruptly declines[4] immediately

[4]Short "jumps" observed in the figures immediately after the volcanic eruption are not real, but a result of the Savitzky–Golay smoothing filter applied on the data [115]. The filter increases the precision of the data without distorting their tendency, by fitting successive sub-sets of adjacent data points with a low-degree polynomial with the method of linear least squares.

after the volcanic eruption to about 20% and then again increases to up to 30% until the end of the LM period. The relative in-degree graph centrality is kept almost constant to about 20% until the end of the LM period, with an abrupt and short decline immediately after the volcanic eruption.

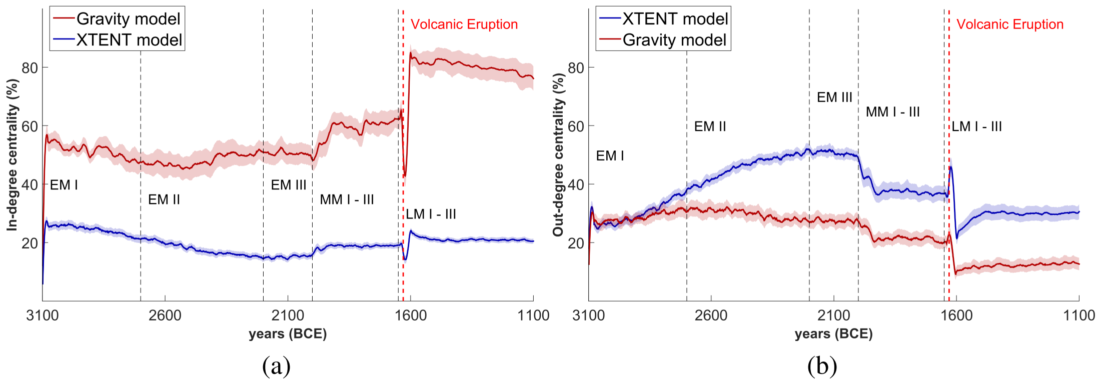


Figure 6.10: (*a*) Relative in-degree and (*b*) relative out-degree graph centrality indexes of the trading network over 2,000 yearly time steps (Minoan period), considering the XTENT and Gravity spatial interaction models.

Low relative in-degree graph centrality rates observed during the EM and MM periods (under XTENT) suggest that there are no clearly "prominent" settlements, meaning that, there are no central attractors considering the other settlements in the trading network. On the other hand, the in-parallel high relative out-degree graph centrality rates during the same period, indicate that there are a few settlements that are considered influential in terms of resource distribution. Therefore, one could assume that a settlement organization of distributing resources by these influencial settlements in the trading network is implied, at least before the volcanic eruption of Thera or the LM period.

Using the Gravity model, the relative in-degree graph centrality gradually increases from about 40% to 75% until the end of LM period, however, with an abrupt fall and rise immediately after the volcanic eruption (Figure 6.10a). By contrast, the relative out-degree graph centrality slowly decreases from about 30% to 15% during the whole period, with an abrupt decline immediately after the volcanic eruption (Figure 6.10b). These high relative in-degree graph centrality rates (under Gravity) suggest that there are only a few “prominent” settlements in the network, implying the possibility of a settlement hierarchy where resources are traded towards these important settlements by other settlements in the trading network. Notice however that this assumes an “attractiveness” of the sites given their W_i importance defined via Equation 6.2, and not the known category of the archaeological sites. In the next section, we see that the “conclusions” obtained with the Gravity model are quite different when the real sites’ category is taken into account; and that in that case they are more in agreement with those of the XTENT model.

Moreover, the relative graph centrality based on *betweenness* is considerably low regarding both XTENT and Gravity models, as presented in Figure 6.11a. This means that most of the trading connections can be made in the trading network without the aid of an intermediary settlement. Thus, there do not appear to exist settlements with much potential of controlling the inter-settlement trade. As such, there is a need to further study if there are other group formation phenomena at work, which need to be captured.

Studying the average clustering coefficient of the trading network graph (Figure 6.11b), we observe that when the Gravity model is employed, it is relatively low (below 40%) until the beginning of LM period, while it is relatively high after the volcanic eruption (more than 40%) until the end of the LM period. When the XTENT model is employed for the trading process, we observe that the average clustering coefficient of the network graph gradually declines from about 50% to 10% until the end of middle EM period; however, it then gradually increases to about 40% until the end of the LM period, with an abrupt and short fall immediately after the volcanic eruption.

Thus, for both the XTENT and Gravity models, the observed settlement trading clustering behaviour after the volcanic eruption until the end of LM period, implies a more dense trading activity between settlements at the time, raising the possibility of more settlement clusters in the trading network. Assuming that such settlement clusters were around large towns, cities, or palaces, this trading network clustering behaviour has a correspondence to the archaeological record (Figure A.1, Appendix A), since just

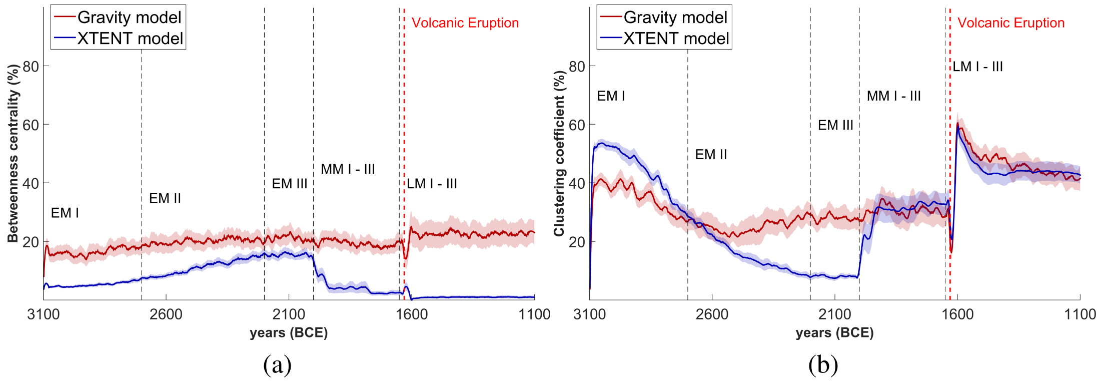


Figure 6.11: (a) Relative betweenness graph centrality and (b) average clustering coefficient of the trading network over 2,000 yearly time steps (Minoan period), considering the XTENT and Gravity spatial interaction models.

two cities are known to have existed during the EM period (*Archanes* and *Knossos*), while several large towns, cities and palaces were flourishing in the area during the MM and LM periods (*Knossos*, *Malia*, *Archanes* and *Galatas*).

Finally, for interest, we also conducted additional experiments considering the same simulation scenarios, however, with a higher percentage of stored surplus trading scheme, *i.e.* ps =80%. Simulation results exhibit similar behaviour with no remarkable differences, besides the average storage per household agent, where even lower amounts of resources stored are observed for the scenario of trading a higher portion of stored surplus. Corresponding results figures are presented in Appendix C, since their behaviour is entirely similar with simulation scenarios considering a lower percentage of stored surplus trading scheme. This similarity in the trading behaviour observed in the results where ps = 80% is justified, since the trading network structure naturally takes into account only the number and density of trading interactions between settlements, and not the volume of resources exchanged within the trading network as well.

In all of the above simulation scenarios, we used attributes relating to settlement's population and lifetime during the simulation period for calculating the importance W_i of a settlement i, given Equation 6.2. In the following simulation scenarios, we fix the

W_i values with known archaeological site categories. This will enable us compare the settlements trading network organization structure developed, based on archaeological estimates on settlement types, with the one autonomously developed during the simulations described above.

6.4.2 Site category bias

Let us first assume a simple, broad classification of settlement types rather than specific site categories, which corresponds roughly to the site hierarchy put forward by [39], based on archaeological estimates: *village* (or settlement or hamlet), corresponding to less than 3.5 ha in size, hosting fewer than 88 households / 875 inhabitants on average; *city* (or large town or town), corresponding to less than 25 ha in size, having fewer than 625 households / 6250 inhabitants on average; and *palace* (or capital town), corresponding to greater than 25 ha in size, with more than 625 households / 6250 inhabitants on average. Based on this classification of settlement types, instead of using Equation 6.2, we express W_i of any settlement point location i as a weight in [0; 1], by mapping the corresponding known archaeological site type [5] as follows:

- $W_i = 0.5$ when the corresponding archaeological site category is a *village*,
- $W_i = 0.7$ when the corresponding archaeological site category is a *city*, and
- $W_i = 0.9$ when the corresponding archaeological site category is a *palace*

As such, the "attractiveness" or the probability of trade for any settlement in the trading network, is biased by the corresponding *known* archaeological site category. Thus, in the following simulation scenarios, settlement importance is based on archaeological evidence on the settlement type at any any given time step and geographic location. The rest of the experimental setup is exactly the same as the simulation scenarios discussed in the previous section.

[5] We remind the reader that all potential settlement locations correspond to actual settlement sites.

To begin with, simulation results on agent settlements number and size are presented in Figure 6.12 for both the XTENT and Gravity models. We observe that the number of settlements remains relatively constant until the end of the EM period, similarly to the previous scenarios, where settlement importance was calculated by its own dynamic characteristics, *i.e.*, population.

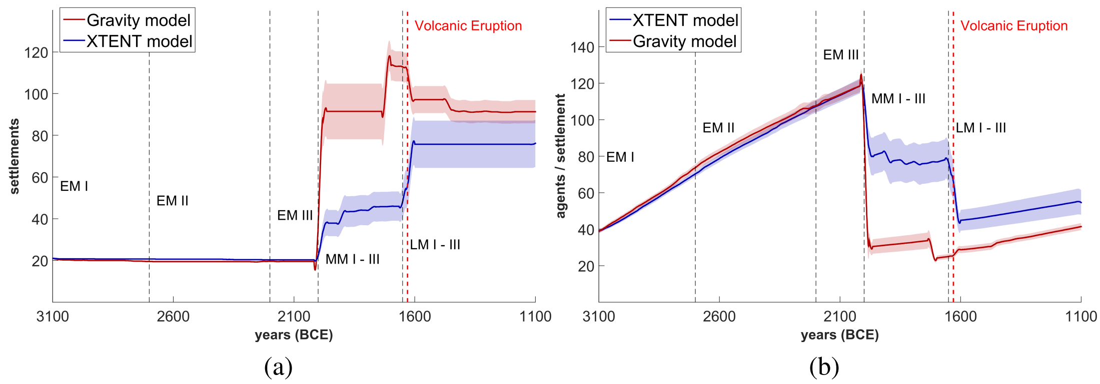


Figure 6.12: (*a*) Number of settlements and (*b*) settlements size over 2,000 yearly time steps (Minoan period), considering known archaeological site categories for both the XTENT and Gravity spatial interaction models.

Regarding the XTENT model, we observe a similar behaviour with scenarios not being biased by site categories, where a gradual increase of settlement numbers over time is noticed, especially during the MM period and even more after the volcanic eruption and LM I period (Figure 6.12a). Similarly, the number of agents per settlement increases until the end of the EM period, and then declines during the MM period. This is due to the high migration rates (because of population growth) observed to more (known) settlement locations available during that period. Moreover, settlement sizes abruptly drop immediately after the volcanic eruption, however, then gradually increase until the end of LM period (Figure 6.12b).

When the Gravity model is employed, we observe a similar behaviour with the XTENT model in settlement numbers and sizes, although the number of settlements slightly declines at the end of the MM period, and drops further immediately after the volcanic eruption; and then remains relatively constant until the end of the LM period

(Figure 6.12a). Thus, in contrast to the previous scenarios, where no bias by known archaeological site categories was introduced, an entirely different behaviour is now observed. That is, a significant difference in settlement numbers is observed, growing up to about 115 settlements during the end of the MM period, and holding up to about 90 settlements until the end of the LM period, while just a number of about 25 and 40 was observed in the previous scenarios (*cf.* Figure 6.8a). We note that this trend in settlement numbers is surprisingly very similar to the one that exists in the archaeological record for the specific environmental area during the whole Minoan period, with the only difference being a substantial decline reported at the end of LM I period in the archaeological record – and which was due to unknown "external" events.[6] Higher values in settlement numbers exist in the archaeological record, suggesting that a higher population growth rate ($> 0.1\%$) probably should have been used during our simulations (we chose to follow [30]).

On the other hand, the numbers of agents per settlement tends to increase until the end of the EM period, and then abruptly declines at the beginning of the MM period from about 120 to 30 households and further decline during the MM III period down to 25. The number of households per settlement, however, is slowly increasing after the volcanic eruption until the end of the LM period, with the Gravity model not being able to achieve higher numbers of household agents per settlement on average than the XTENT model (Figure 6.12b).

We also report that the overall number of households (*i.e.*, the agent population) is constantly increasing during the whole time period, same as in the scenarios without bias from known archaeological site categories, being able to even achieve higher population sizes, from about 820 initial households to about 3500 and 3700 agents for the XTENT and Gravity spatial interaction models, respectively, with only an abrupt and short decline immediately after the volcanic eruption, as shown in Figure 6.13.

[6] Archaeologists assume that a wave of fire destructions affected Cretan settlements during and at the end of LM IB, that have variously been attributed to internal revolt, Mycenaean invasion, or to a major natural disaster involving earthquakes [40].

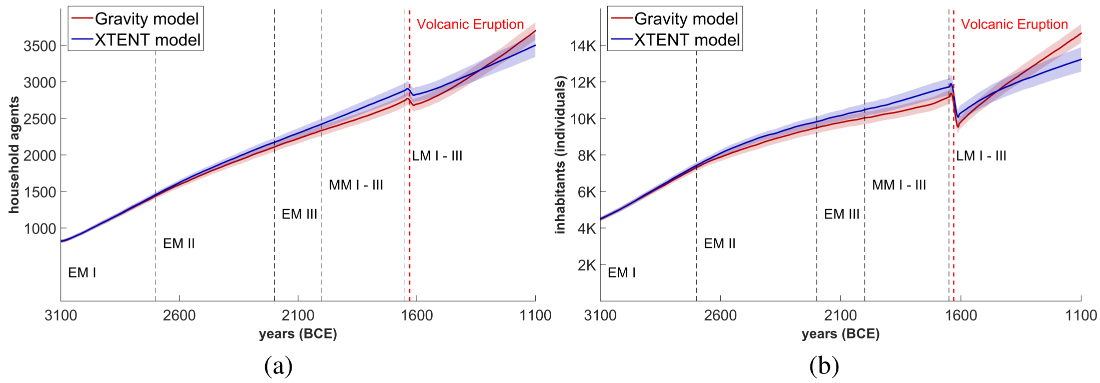


Figure 6.13: (*a*) Household agents and (*b*) inhabitants population sizes over 2,000 yearly time steps, considering known archaeological site categories for both the XTENT and Gravity spatial interaction models.

We note that, when the Gravity model is employed for simulating a trading network, where settlement importance is based on archaeological evidence, it appears to be better in sustaining higher population sizes after the crisis of the volcanic eruption of Thera, with respect to the XTENT model that favours the distance between settlements rather than their importance. This is unlike to what was the case without the site category bias (*cf.* Figure 6.9a).[7]

Regarding the structural behaviour of the settlement trading network, the relative in-degree and out-degree graph centralities are presented in Figure 6.14. The XTENT model exhibits a very similar behaviour to the one without known site types bias (*cf.* Figure 6.10). Interestingly, the Gravity model is now showing a similar behaviour to the XTENT model, that is, it exhibits lower rates of in-degree and higher rates of relative out-degree centrality. The low relative in-degree graph centrality rates during the EM and MM periods, imply that there are no "prominent" settlements. By contrast, the high relative in-degree graph centrality rates observed in the trading network after the volcanic eruption and during the LM period, suggest that there are certain "prominent" settlements in the trading network. On the other hand, the low relative out-degree graph

[7]The corresponding individuals' population size for the case without bias is shown in Figure C.1, Appendix C.

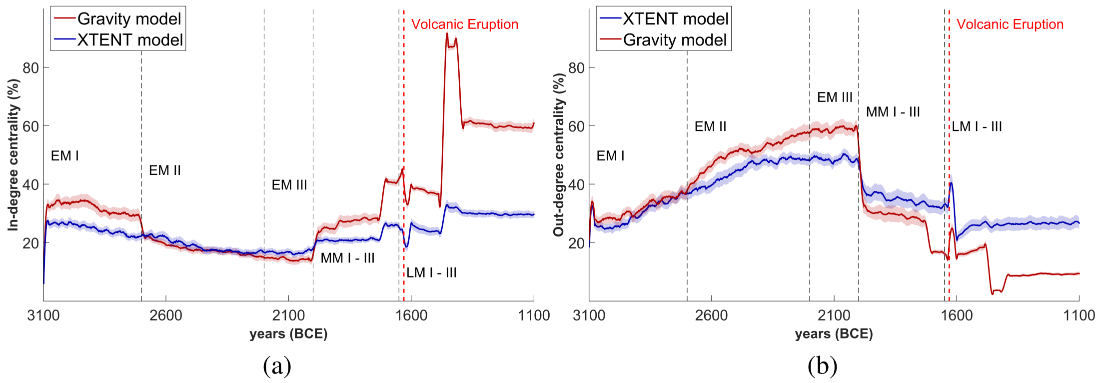
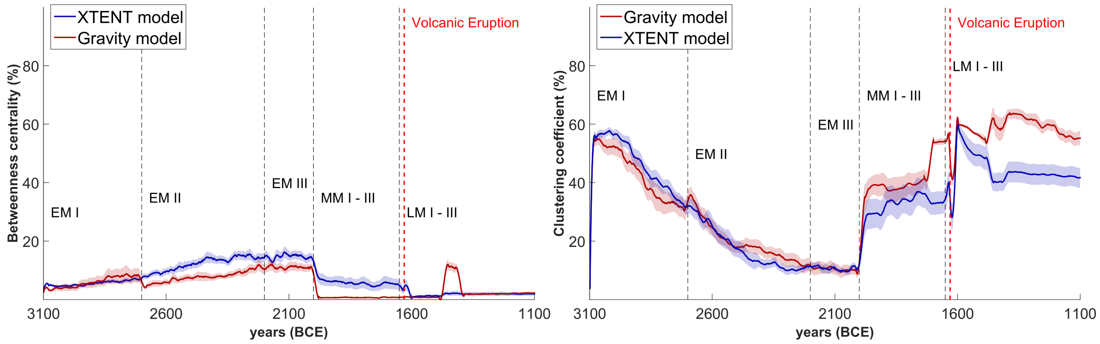


Figure 6.14: (*a*) Relative in-degree and (*b*) relative out-degree graph centrality indexes of the trading network over 2,000 yearly time steps (Minoan period), considering known archaeological site categories for both the XTENT and Gravity spatial interaction models.

centrality rates during the LM period, indicate that there are many settlements with a similar degree of “influence” in terms of resource distribution. Therefore, one could assume that a settlement hierarchy where resources are traded towards the (few) most important settlements in the trading network is implied during the LM period.

Moreover, the relative betweenness network centrality is low for both XTENT and Gravity models, as presented in Figure 6.15a, even lower than scenarios without site category bias (*cf.* Figure 6.11a), suggesting even less potential for control on the flow of resources traded between settlements. However, there is a structural basis for assuming that certain settlements with the highest relative betweenness centrality in the society are “different” from the other settlements in the area, at least during the EM and MM period. Indeed, in Figure 6.16, we show a snapshot of a simulation run during the end of the EM period using the Gravity model, where settlements with the highest relative betweenness centrality (Figure 6.14b) are among the ones with the highest relative out-degree centrality (Figure 6.14a). In such a case, the trading network conceivably has a structure that allows us to assume a settlement hierarchy where resources are distributed by these most influential settlements to others in the network (during the EM period).

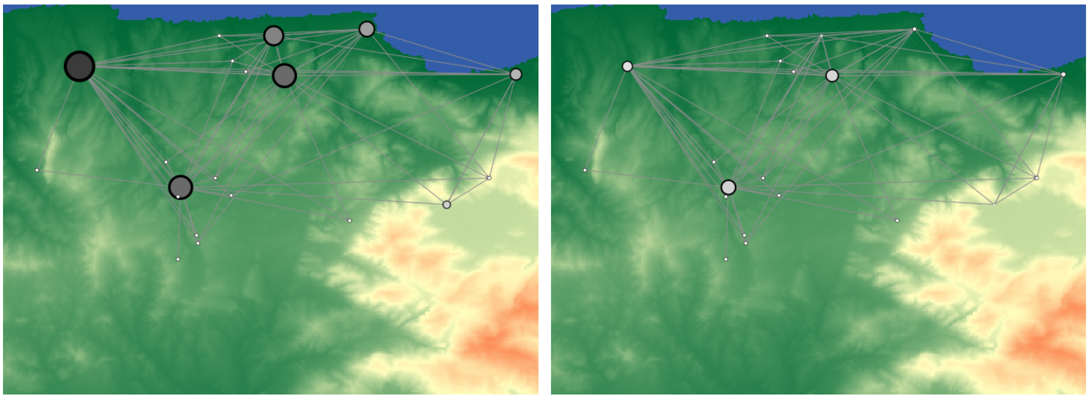


(a) (b)

Figure 6.15: (*a*) Relative betweenness graph centrality and (*b*) average clustering coefficient of the trading network over 2,000 yearly time steps (Minoan period), considering known archaeological site categories for both the XTENT and Gravity spatial interaction models.

Regarding the average clustering coefficient of the trading network graph (Figure 6.15b), we observe that the Gravity model has again a similar behaviour to the XTENT model, that is, it gradually declines from about 50% to 10% until the end of middle EM period, and gradually increases to more than 50% until the end of the LM period, with an abrupt and short fall immediately after the volcanic eruption. The low clusterization thus observed in the trading network until the end of the EM period may suggest that the trading network connections are losing density until the end of the EM period. The network's clusterization appears to be recovered in the MM period, and even more in the LM period, indicating the possibility of more dense settlement clusters in the trading network, where resources are traded towards the few most important settlements within these clusters (those with high relative in-degree graph centrality). There seems to be a correspondence with the archaeological record, enhancing such a possibility—since several towns, cities or palaces are recorded during the MM and LM period, while just a two towns exist during the EM period, as previously noted.

Concluding this section, we remind here the reader that the Gravity model is able to better capture the trend in settlement numbers that exist in archaeological record. This is a reason to believe that, in this case, Gravity allows us to better interpret the structure and dynamics of the formed trading network. The "unchanged" behaviour of



(a) (b)

Figure 6.16: (*a*) Relative out-degree and (*b*) relative betweenness graph centrality of the trading network from a snapshot of a simulation run during the end of the EM period using the Gravity model. Settlement nodes are represented as circles and trading connections as links between them, where their size and color represents their centrality value, from minimum (white) to maximum (black).

the XTENT model is justified, since it favours the distance between settlements rather than their importance. Thus, it should be used in cases where settlements importance is not known, or cannot be properly modeled.

6.5 Conclusions

In this chapter, we presented an artificial community trading module for modeling inter-settlements interactions, incorporated to our developed ABM system that we provide for archaeological simulations.[8] In particular, we model inter-community trading interactions by incorporating a trading sub-model, employing two well-known spatial interaction models, XTENT and Gravity. The simulations' aim was to assess the sustainability of the artificial society in terms of population size, number and distribution of agent communities with respect to both spatial interaction models, to analyse the resulting trading network structure during its evolution over time, and to draw interesting conclu-

[8]The source code of the ABM and its associated data are available here.

sions (or, rather, sketch out interesting hypotheses) about the settlements' hierarchy, via annotating our results with the archaeological record. Although in this work we consider the density of trading interactions between agent communities in the network, we intend in the future to represent the dynamic trading network as a "weighted" directed network graph, in order to also take into account the amount or volume of resources exchanged during trade.

As a case study we considered the Bronze Age Minoan civilization and as the ABM's environmental area we considered the geographic area of the wider region around Knossos, located in the central part of the island of Crete, Greece. Simulation results show that when settlements' importance is known or properly inferred (based on archaeological data or evidence), modeling a trading network relying on the Gravity model can produce settlement patterns similar to the one that exist in archaeological record for the area under study (see Figure 6.12a), since it favours settlements importance rather than the distance between settlements. Otherwise, if solely settlement locations are known, then the XTENT model can produce acceptable results on simulating the trading activity between them.

When the known sites' importance is used in our simulations, the high relative out-degree centrality rates observed in the trading network, along with the low clustering coefficient observed during the end of the EM period, suggests that a small number of influential centres could have existed, linked to a settlement hierarchy where resources are distributed by these influential settlements to others in the network—but there are no clearly prominent centres to which resources are directed. Interestingly, after the catastrophic event of the volcanic eruption of Thera and during the LM period, the trading network connections are becoming much denser, and resources are now being distributed towards only a few settlements in the network. We note that these results are in line with archaeological theories suggesting that already during the EM period regional powers existed in the area, while after the MM period the actual settlements hierarchy was transformed, with subsequent radical changes in their trading network, affected by settlement numbers and sizes as well as natural disaster events (as also indicated by Figures 6.14 and 6.15 in our work here). Specifically, archaeologists argue that independent political units and centres of the EM and early MM period, were incorporated into a ”Knossian” state during late MM and early LM periods by being demoted to secondary centres while others were promoted from tertiary to secondary centres in an attempt to undermine local traditional power relations, rendering, thereafter, the system unstable and hence vulnerable [40]. Thus, large and comparatively well integrated polities that existed until the end of the MM period in Central Crete were incorporated into a larger political framework and a territorial state headed by Knossos [39]. Given the above simulation results, our ABM appears to be able to provide support for those theories to some extent.

Chapter 7

Conclusions

In this thesis we presented a novel ABM system for delivering insights and “in silico” interpretations for archaeological inquiry, regarding the social dynamics of artificial past societies, and based on the archaeological record for the geographic space and era under study. Building a computational model from an archaeological theory is not a trivial matter, while formal theories are often too wide ranging to be put into computational terms. One major issue with agent-based modeling in archaeology, is that the state-of-the-art models oversimplify agency, and do not define agents in the way these are defined in the MAS community; and thus, do not allow essential agent features, such as *autonomy* or *interaction ability*, to appear in the actual system implementation. Social scientists and archaeologists, however, are interested in understanding human societies, in particular the mechanisms that allow these systems to self-regulate, and the processes that shape and form their internal structure and organization. Thus, it is not the benefit of such an endeavour to diminish the autonomy of the agents or to drop it from the model altogether.

Accordingly, we equip social archaeologists with *AncientS-ABM*, an autonomous agents-based simulation system that is flexible and open, enhanced by ideas and approaches from Computer Science and MAS. Agents in our ABM system are endowed with a *utility-based* architecture and can incorporate self-organization mechanisms and game-theoretic approaches that allow for strategic agent interactions and the dynamic modification of the organizational characteristics. Simulation results demonstrate that it can be readily applied in large, real-world geographic environments and time periods, delivering "macroscopic" structures that can provide insights or suggestions for the assumed theoretical ones, and help achieve better utilization of archaeological data on various "microscopic" hypotheses, regarding the artificial past society organization. Besides archaeology-related fields, our ABM can be used as the basis for application systems to other (computational) social sciences fields that span from social networks, to education, to epidemiology, and to environmental and human geography, as we elaborate below. Indeed, the space for modifications, extensions and applications of this work is very rich.

This final thesis chapter is organized as follows. Section 7.1 provides a summary of our thesis, highlighting the most important points linked to each chapter. Then, in Section 7.2 we discuss potential extensions of our research, as well as its application to other computing or non-computing disciplines.

7.1 Thesis Summary

In the beginning of this thesis, we introduced the reader on the importance of understanding the evolutionary emergence of human social organization and the inherent uncertainty that exist in archaeological theories regarding early and past societies. Specifically, we set the theoretical background behind our research, and stress the weakness of current agent-based simulation systems on modeling the internal structure towards the formal design of agency. Most existing ABM frameworks in archaeology consider a simple (reflex) agent design in order to avoid the aggregate problem becoming too difficult to be examined (mathematically). We present and provide an agent-based modeling framework, rooted in MAS approaches towards agent organizational design, and propose detailed solutions for each shortcoming encountered, by utilizing methodological approaches from other computer science-related fields (such as graph theory), as well. For each of the proposed solutions, we conducted extensive simulations of the respective enhanced ABM to evaluate both the theoretical mechanisms themselves in terms of their modeled behaviour accuracy, and their effect on the organization and evolution of the artificial past society, based on the archaeological record of the simulated past society and era. Simulation results indicate that the incorporation of our methods can lead to "macroscopic" structures that are able to provide insights and deepen our understanding on the processes leading to emergent organization patterns at different levels of the artificial society. In particular, results demonstrated that when agents adopt an "egalitarian" social organization paradigm, the emerging development of many "small-size" settlements appear to be the way for survival over time; when the "self-organization" social paradigm is adopted, a "heterarchical" social structure emerges, giving rise to larger settlements during their evolution.

In more detail, in Chapter 3, we presented in detail the core of a readily applicable ABM framework for simulating the social dynamics of an artificial society of agents. We implemented autonomous, *utility-based* agents (rational utility-maximizers) for modeling their intra-community interactions, unlike most existing ABMs in archaeology. Although our ABM system is currently limited to cultivation and migration agent actions only, we do incorporate a number of different social organization paradigms and cultivation systems in our modeling approach. Most importantly, we presented an agent organization paradigm of agents *self-organizing* into a "stratified" social structure, and continuously re-adapting the emergent structure, if required. The proposed self-organization algorithm comes with desirable theoretical properties, specifically agent spontaneous re-organization, without any external control, and robustness to changing conditions, thus enhancing agent survivability. We also note that, this is the first time that a self-organization approach is incorporated in an ABM system used in archaeology. We further defined an (intelligent) agent decision-making process, using an MDP to decide on migration (or settlement) policies. We conducted a systematic evaluation of the influence of the various social organization paradigms on the artificial past society, in terms of population sustainability and agent community sizes, aiming to study the historical social dynamics. As a case study, we employed our ABM system to assess intra-settlement organization of an artificial Minoan society residing at the wider area of *Malia* at the island of Crete during the Bronze Age. Model parameters were initialized based on available archaeological data on the area and period under study. Simulation results demonstrate that self-organized agent populations were the most successful, growing larger than agents employing different social organization paradigms, indicating that a *heterarchical* social structure, having emerged by the continuous readaptation of social relations among Minoan households, might well have existed in the area of study. This fact is in line with archaeological evidence for larger settlements (towns and palaces) eventually coming to existence during the MM–LM period, where a more varied and dynamic social structure is now suggested [41].

Furthermore, in Chapter 4, we presented an alternative self-organization agent organization paradigm, by incorporating an evolutionary game-theoretic approach for modeling the evolution of strategic behaviours in a population of self-organized agents. The reason was a main drawback on the specification of the internal "microscopic" structure of agent organization, in which a cooperative attitude on behalf of the agents was assumed, willing to always provide available resources out of their stock to help other community members in need. In particular, we provided an novel evolutionary self-organization algorithm by simulating repeated "stage games" played by pairs of *strategic* agents, assuming cooperative, defective and equivalent retaliation strategies on behalf of the agents, being also able to adopt other strategies over time. Agents in our ABM system required to receive non-static payoffs and their population was not constant during simulation, in contrast to most matrix games studied in the literature, thus we formulated the evolutionary dynamics based on evaluating agents', rather than strategies' fitness. We also assumed different variations for agent fitness function and strategy review and adoption processes. We finally conducted a systematic evaluation of the performance of strategic household agents operating in Minoan artificial communities, by studying the evolution and adaptation of strategic behaviours and the effect these have on the sustainability of the Minoan society as a whole. Simulation results indicate that agent populations are better sustained when agents base their strategy review decisions on the relative success of their current strategy with respect to the success of agents employing the same strategy in their settlement community, and when strategy adoption is stochastic, rather than deterministic. Interestingly, in those scenarios, agent populations also converge to adopting cooperative strategies, despite this behaviour being in contrast to their stage game equilibrium.

In Chapter 5, we incorporated a natural disaster module in our ABM system, for assessing the imminent social crisis on the artificial agent society. Specifically, we utilized spatial analysis techniques for the specification and development of the respective component, implementing a volcanic eruption catastrophe, that captures associated sudden-onset (tsunami) and slow-onset (volcanic ash) disasters. We employed our extended ABM system to assess the impact of the natural disaster on different social organization behaviours, along with population sustainability of Minoan household agents, in terms of agent community numbers and sizes, migration behaviour and agents strategic behaviour evolution, before and after the catastrophic event. We also conducted a systematic evaluation of several natural disaster scenarios on social change, based on archaeologically traceable environmental and human impact of the mid-2nd millennium BCE Santorini eruption to the Minoan civilization. Simulation results demonstrate that "self-organized" household agents are able to sustain themselves after the volcanic eruption, however, with noticeable changes in the settlements' distribution. A strong impact on social behaviour is further observed, transforming the initially cooperative agents' behaviour to a non-cooperative one, suggesting that the Theran eruption led to a gradual breakdown of the Minoan socio-economic system.

Finally, in Chapter 6, we further extended our ABM system by incorporating a novel "trading" module for simulating agent inter-communities trading interactions. We employed the trading module with two different spatial interaction models, the *XTENT* and

Gravity, for studying household agent settlements' trading network, considering as a case study the Minoan society during the Bronze Age, in the wider area of *Knossos* at the island of Crete, Greece. We conducted a systematic analysis of the trading network formulated over time, given agent settlements geo-location and position within the trading network, and the structural properties of the network itself, by utilizing graph theory. We interpreted simulation results in terms of the network's potential centralization, clustering behaviour or potential settlement organization during the whole simulation period, and intuitions were provided regarding the appropriateness of the different spatial interaction models.

Simulation results demonstrated that modeling a trading network by employing the Gravity model, thus, giving more weight to the "importance" of settlements than to the distance between them, macroscopic settlement patterns appear to be similar to the ones that exist in the archaeological record. However, this is most appropriate when the importance of settlements is known or can be derived based on archaeological data, otherwise, when settlement locations are only known, then the XTENT model is is probably adequate, favouring as it does the distance between settlements and not than their importance. Results also indicated that the evolution of the values of the graph-theoretic indices characterizing the settlements' trading network was affected by the Theran volcanic eruption. In particular, it appears that the network's structure and interaction patterns are to an extent reversed after the Theran eruption, when compared to those in effect in earlier periods.

As a note, we stress that all of our ABM simulation results do not aim to prove or disprove any particular archaeological theory; the potential congruence between simulated macroscopic structures and the ones assumed in certain archaeological hypotheses proves, however, our ABM's "generative sufficiency", without of course excluding the fact that (partially) alternative "microscopic" specifications could equally generate similar macroscopic structures and dynamics [45]. Regardless, we believe we have adequately shown that our work can provide researchers with useful intuitions, and can be used to test and provide support to alternative or competing archaeological hypotheses. What is left is to further enhance our ABM and deploy it in different past societies and eras, or even in other disciplines and fields, as we explain below.

7.2 Future Research Directions

Our work in this thesis opens up a host of possibilities for future work, and opens the way for entirely novel research directions.

To begin, our framework allows one to run more simulation scenarios with a variety of initialization setups. This is useful due to the conditional nature of agent-based simulation's results, that is, their dependency to the input values. As such, one needs to conduct "calibration" when sufficiently detailed empirical data available to "fix" the values of the parameters; or to conduct a sensitivity or "robustness" analysis, to determine the results' dependency on the internal structure of the ABM [91]. We have already conducted and presented a basic sensitivity analysis for our ABM (*cf.* Section 4.4.5 and also Section 3.4.2), but a more extensive one would be useful for evaluating how sensitive our simulation results are when varying additional ABM parameters. Such parameters may include more or fewer number of agents with different ranges of migration capabilities, different cell output values per cultivation system or different aquifer proximity radius and resettlement cost values, and so on.

An interesting extension of our work would be to equip our ABM with an additional environmental module, able to incorporate environmental information such as vegetation data, geological information, or reconstructed climatic data, in case any such kind of information is available for the case study under examination. This would allow one to model additional agent–environment interaction processes.

Moreover, future extensions include modeling additional types of agent utility-generating activities besides cultivation, such animal husbandry, hunting or even fishing in environmental locations near coastline areas. It is also interesting to incorporate formal mechanisms for modeling the use of advanced equipment, craft specialization, or variable manpower. To this end, different types of agents with corresponding skills can also be employed or even emerge during the simulation, such as administrators, craftsmen or religious practitioners, depending on the overall agricultural surplus of an agent organization, parameterized based on available archaeological or historical records regarding the political and economic relations of the respective case study under examination.

Furthermore, one could employ our ABM to examine additional (perhaps highly complex) strategic behaviour used by agents during exchanges in the resource distribution game (*cf.* Section 4.2), both at the household or settlement level. Moreover, an agent can be modeled to play the resource distribution game with a specific number of other agents in the organization, based on some probability, in the occasion of large-scale simulation experiments, lowering as such the computational time needed to perform such extensive simulations.

Additional mechanisms for resource exchange and trade can be also incorporated in our ABM framework. A more elaborate trading module could for instance include trading processes from external sources. We already have a specific plan regarding how to extend our trading model to include maritime/sea trade, and its effects in coastal settlements; rendering potentially higher surplus resources, thus agent utility, in those settlement locations than others in the mainland. It could also consider the proximity to religious centres or peak sanctuaries, and based on a sample from a noise distribution for specifying additional trading resources. In particular, the amount of resources U_i^{ext} that a settlement i receives by external trading can be formulated as:

$$U_i^{ext} = W_i \cdot G(\mu, \sigma) / {D_i}^{\rho} \tag{7.1}$$

where W_i is the importance of settlement i, G is the value of a sample from a Gaussian noise distribution with mean μ and standard deviation σ, based on the overall amount of surplus resources at the current time, D_i is the (minimum) distance from settlement i to the coastline or to the religious center (peak sanctuary), and ρ is a constant used to adjust the required level of the effect that the importance W_i of settlement i and the distance D_i have on the overall trading interaction, that is on the acquisition of external additional resource by settlement i (similarly to Equation 6.5). Of course, such a mechanism has to also be parameterized based on available archaeological data for the artificial society under study, and potentially to be affected or informed by the enabled instance of the natural disaster module (*i.e.* the volcanic eruption of Thera, in this case study).

Moreover, we intend to run simulation scenarios on (artificial) past societies in different geographical space and time, where sufficient archaeological data is available for testing and assessing ABM results with respect to related archaeological hypotheses regarding their social organization. For example, it is of much interest the social organization during the Ottoman centuries in the island of Crete (*ca.* 17th–19th c. CE), where a complete historical record exists, regarding multi-cultural habitation sites, census data, inhabitants religion and numbers, and so on.[1] Another case study is the "Neolithic Thessaly", Greece, a significant region for the understanding of the development of the gradual Neolithization of Europe around *ca.* 6000 BCE, where related habitation sites are available—however, with scarce information regarding their intra- and inter-community social organization.[2] Moreover, a recent research project has been initiated aiming to examine the social dynamics of early Egypt, based on an ABM approach.[3]

We also aspire to deploy our ABM as a fully modular archaeology agent-based simulation system on the web, that can be extensible and able to easily carry out simulations for a given sort of archaeological hypothesis and theory, regarding the social organization and trading behaviour in past societies—in small and wide exchange networks, and in any geographical area of interest. However, since the entire process will need higher performance than one could get out of a typical workstation, there is a need to employ

[1] The historical record is available by the GeoSat ReSearch laboratory from the Digital Crete project (http://digitalcrete.ims.forth.gr).

[2] The archaeological record is available by the GeoSat ReSeArch laboratory form the IGEAN project (https://igean.ims.forth.gr).

[3] For more information on the project visit http://www.nitschke-lab.uct.ac.za/nitschke/research.

additional computational power, by utilizing the power of *high performance* or *Grid computing*, where specific instances of the ABM and corresponding simulation scenarios can be allocated to dedicated cluster nodes, delivering aggregated ABM results in an efficient and practical way to the end-user. Scholars using the system would be able to add and manipulate components and agent and system-level parameters, in order to test and obtain intuitions and insights about the implications of their own behavioural and environmental assumptions.

On the other hand, our work can be also adopted in alternative application areas. Our ABM approach is rooted in MAS and can be effectively used in (computational) social sciences and sociology-related areas, that span from social networks, to education, to epidemiology, and to environmental and human geography. Social networks and their analysis can take advantage of our utility-based self-organized agent organization paradigm, where agents can be represented as nodes in the social network graph. In general, social networks are indeed self-organizing, emergent, and complex, and macroscopic patterns may appear from the local interaction of the agents (nodes) that make up the network system [97]. Moreover, the "power distance" notion in our (evolutionary) self-organizing algorithm (*cf.* Section 3.2) can also be utilized to study the evolution of social norms, or the conditions under which social norms will be established eventually in "dynamic" agent networks, thus, the convergence to certain social norms (see a primary example in [45]). In addition, the geospatial aspect of our ABM system, along with the incorporated social organization paradigms and spatial interaction models can also assist the demographic behaviour and analysis of a given existing or historical (agent) population residing at a specific landscape: for instance, one could modify and employ our ABM to study spatial or temporal changes in response to real quantifiable agent data characteristics (such as birth, death, migration, aging, and so on) [13].

Furthermore, the ABM system can be also readily adapted and incorporated in education-related systems. A learning framework can be developed based on our approach, one that will allow students in primary and secondary schools to explore the organization of past societies within a real geographic environment, and to study their evolution in time and explain the dynamics that guide this evolution. Such a framework can promote coding and computational thinking in schools via, for instance, "serious gaming" in which students can explore an ancient civilization based on the available archaeological evidence and historical records, promoting inquiry-based learning, and offering the ground of rich explanations and insightful interpretations regarding existing archaeological or historical theories.

Another research direction can be the use of our (adapted) ABM for epidemiology—that is, for the study of epidemic dynamics, depicting at the same time the spatial spread of a disease. The model can provide a systematic way to evaluate competing intervention strategies, as well as to design an effective policy response, based on the different agent types and relations provided by our self-organization algorithm, thus giving rise to different susceptibility levels (for a recent example see [50]).

Another promising area for extending our research is geography and ecology. Our geospatial ABM can provide the core of various agent-agent and agent-environment interactions for studying the influence of an artificial agent society has on the space they occupy, and also could be informed by a complete geostatistical analysis [83, 84]. Moreover, several aspects of our ABM approach, such as the utility-based agent architecture, can also be adapted in order to assist in urban planning and growth, and in the general modeling of processes related to residential development within an urban system (for example see [16, 113]).

As a final note, we consider our work to be a stepping stone towards a greater vision with three axes or plans of action: *(i)* to pursue the study and formulation of archaeological theories and hypotheses on the organization of past human societies; *(ii)* to provide intuitions, ideas, and algorithms for modeling agent organizations and the emergence of agent collaboration in MAS; and *(iii)* to focus on devising novel algorithms for adaptation and self-organization methods, with potential application on interdisciplinary agent-based models.

Appendix A

Case Study's Archaeological Data

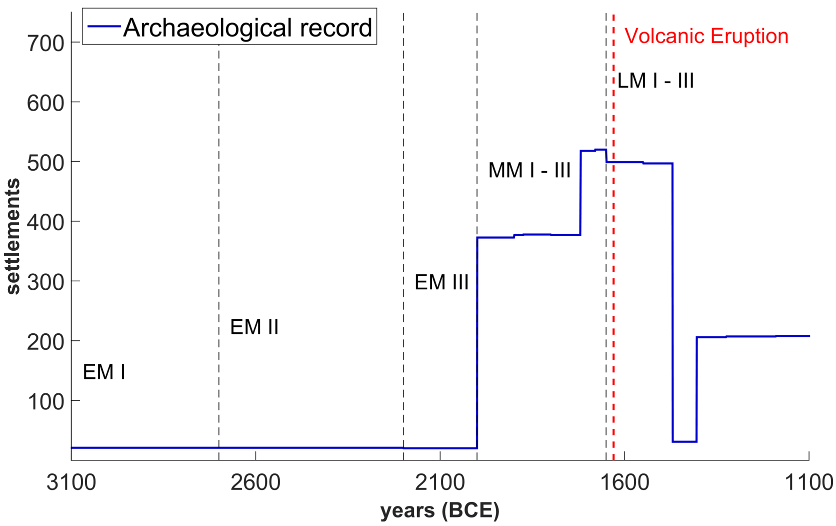


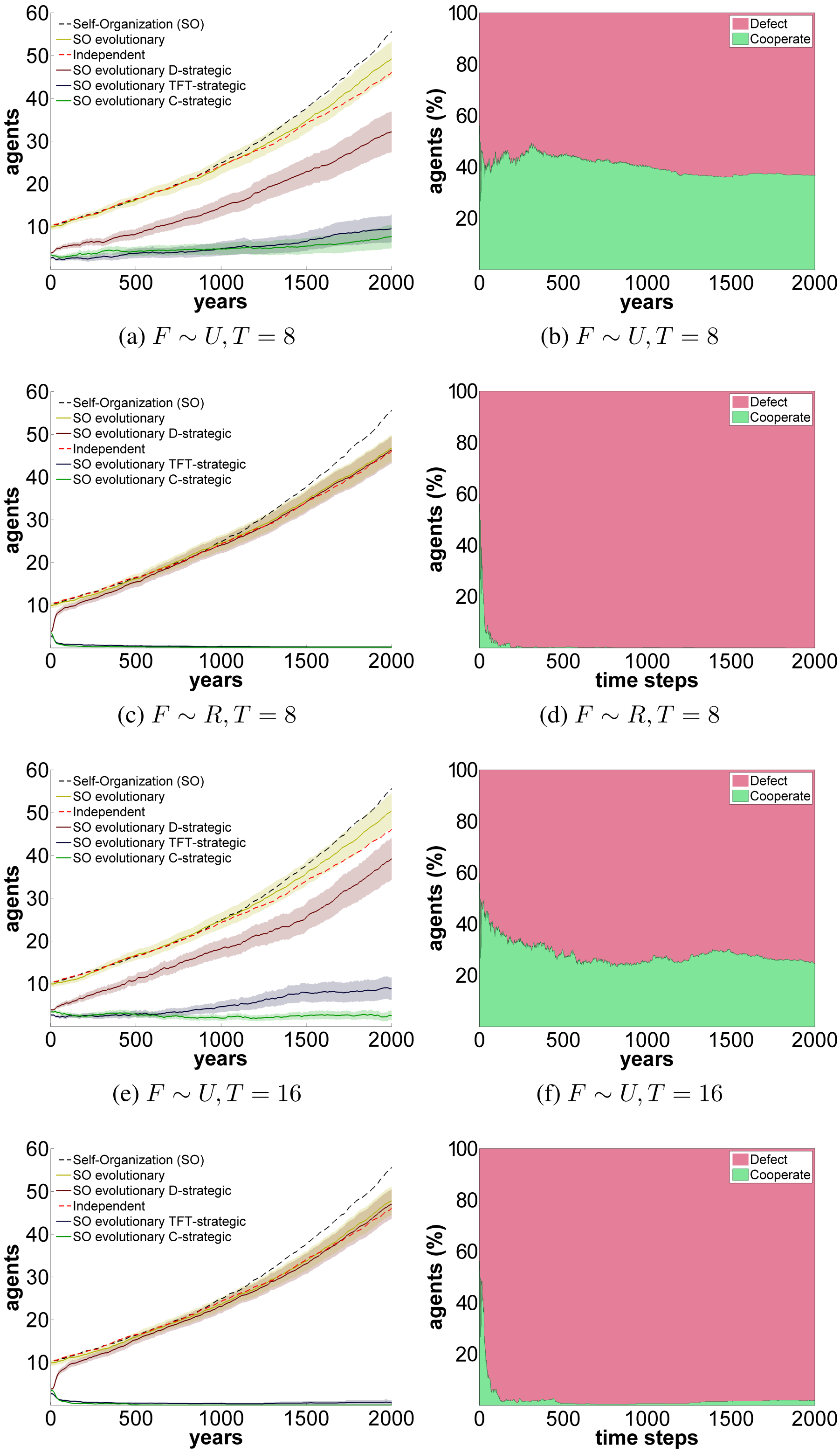
Figure A.1: (*a*) Settlement numbers that exist in the archaeological record for the modeling area of Chapter 6, during the Minoan period. Data were provided by the GeoSat ReSeArch laboratory from the "Digital Crete" project.

Chronology (Platon)	**Relative chronology**	**Manning (1995) [90]**	**McEnroe (2010) [93]**	**Simplified date**
Protominoan Age	**Early Minoan**			
Phase I	*EM I*	3100 - 2700	3100 -	3100 - 2700
Phsae II	*EM II*	2700 - 2200	- 2200	2700 - 2200
Phase III	*EM III*	2200 - 2050	2200 -	2200 - 2000
Minoan Age (Palace period)	**Middle Minoan**			
Pre-palace	*MM IA*	2050 - 1925	- 1900	2000 - 1900
Old-palace Phase I	*MM IB*	1925 - 1900	1900 -	1900 - 1875
Old-palace Phase II	*MM IIA*	1900 -	-	1875 - 1800
Old-palace Phase II	*MM IIB*	-1750	- 1750	1800 - 1720
New-palace Phase I	*MM IIIA*	1750 - 1700	1750 -	1720 - 1680
New-palace Phase I	*MM IIIB*	1700 - 1675	- 1700	1680 - 1650
	Late Minoan			
New-palace Phase II	*LM IA*	1675 - 1600	1700 - 1580	1650 - 1550
New-palace Phase II	*LM IB*	1600 - 1490	1580 - 1490	1550 - 1470
New-palace Phase III	*LM II*	1490 - 1435	1490 - 1360	1470 - 1405
Post-palace Phase I	*LM IIIA*	1435 - 1360	1360 -	1405 - 1325
Post-palace Phase II	*LM IIIB*	1360 - 1200	- 1200	1325 - 1190
Post-palace Phase II	*LM IIIC*	1200 - 1100	1200 - 1100	1190 - 1100

Table A.1: Absolute and relative chronology and dates for the Minoan period (BCE) suggested by archaeologists, along with the simplified (conventional) date used in our ABM simulation scenarios.

Appendix B

Additional Simulation Results for Chapter 4



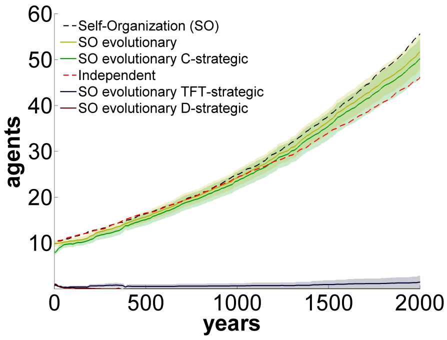
(a) $F \sim U, T = 8$ (b) $F \sim U, T = 8$

(c) $F \sim R, T = 8$ (d) $F \sim R, T = 8$

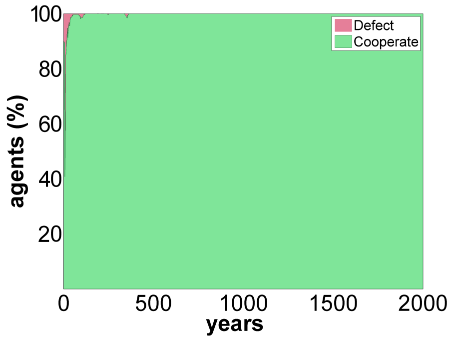
(e) $F \sim U, T = 16$ (f) $F \sim U, T = 16$

(g) $F \sim R, T = 16$ (h) $F \sim R, T = 16$

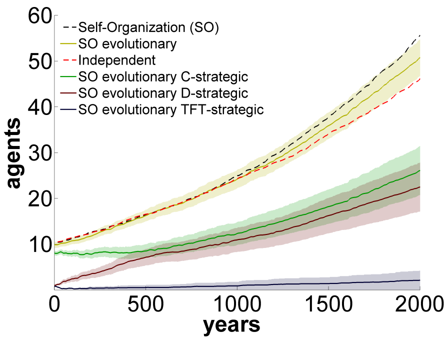
Figure B.1: Agent population (*right*) and percentage of average cooperative and defective behaviour of strategic agents (*left*), including that of TFT agents), for scenarios with *deterministic* strategy review and F calculated across agents in the *settlement* that share the *same strategy*.



(a) $F \sim U, T = 8$

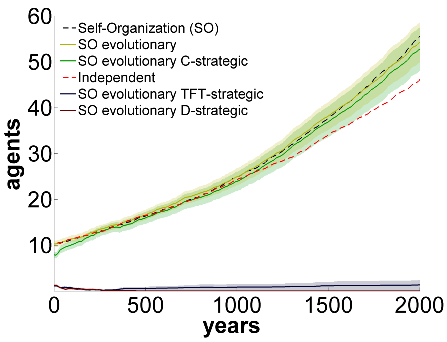


(b) $F \sim U, T = 8$

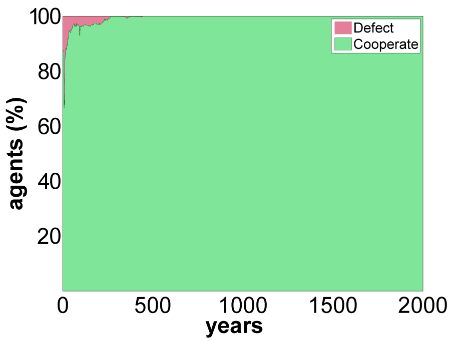


(c) $F \sim R, T = 8$

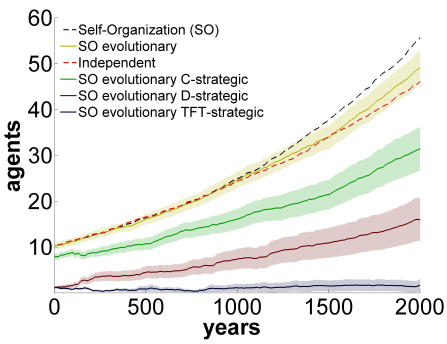
(d) $F \sim R, T = 8$



(e) $F \sim U, T = 16$



(f) $F \sim U, T = 16$



(g) $F \sim R, T = 16$

(h) $F \sim R, T = 16$

Figure B.2: Agent population (*right*) and percentage of average cooperative and defective behaviour of strategic agents (*left*), including that of TFT agents) for scenarios involving an initial rate of 90% of C-strategists, with *stochastic* strategy review and F calculated across agents in the *settlement* that share the *same strategy*.

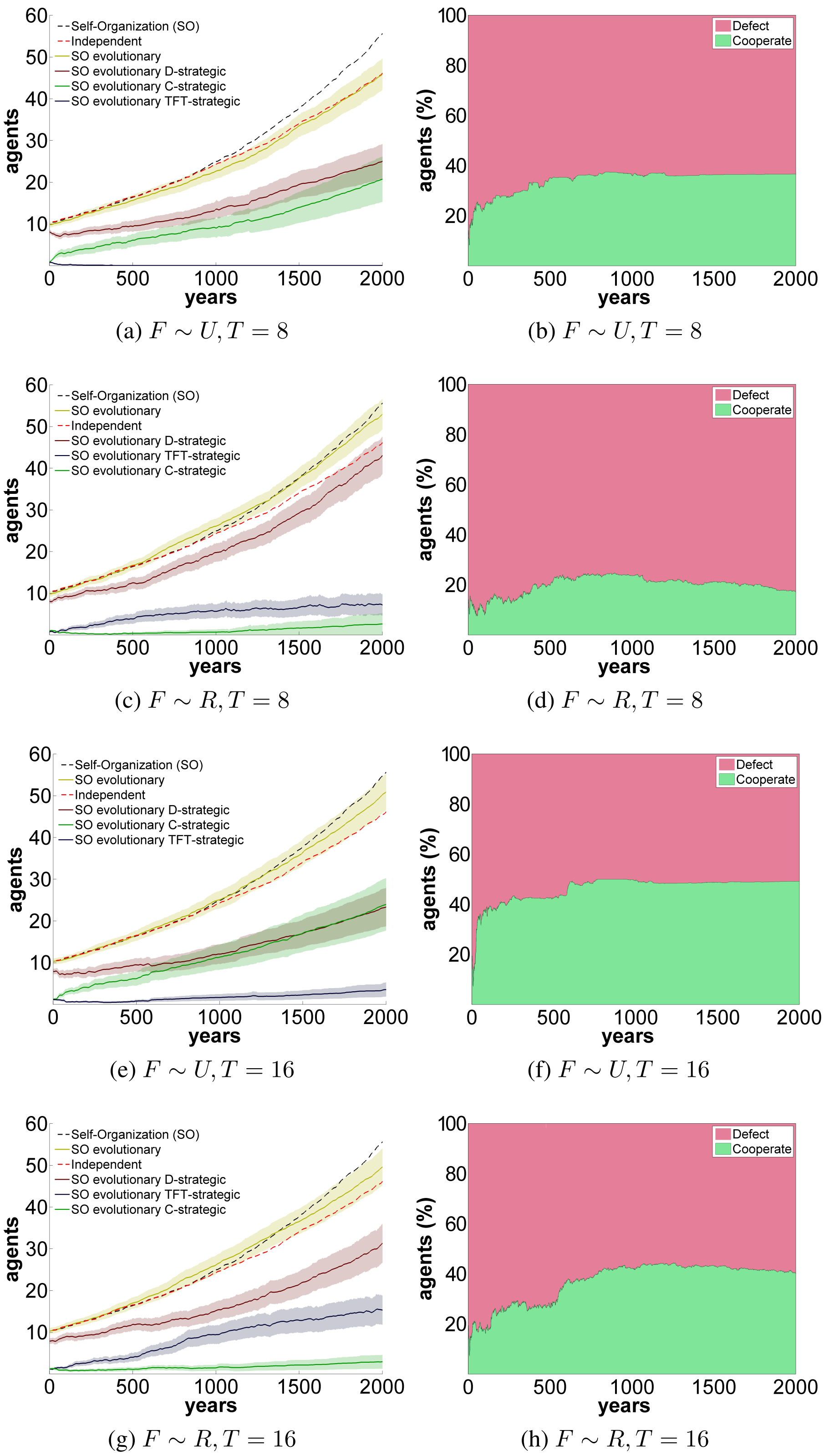
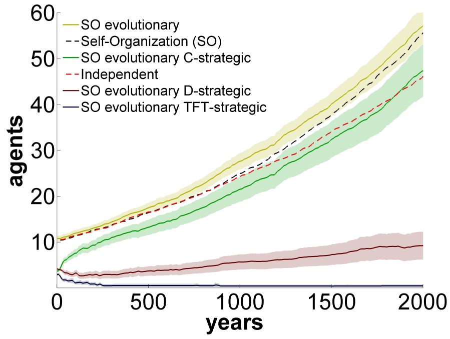
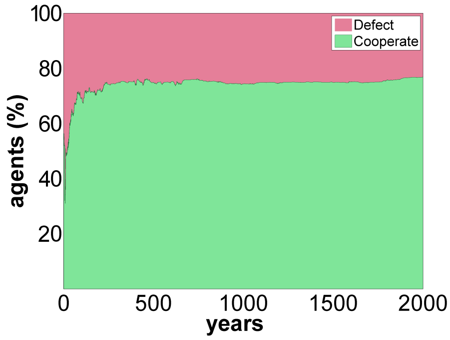


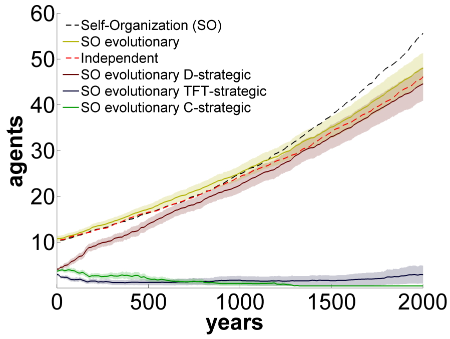
Figure B.3: Agent population (*right*) and percentage of average cooperative and defective behaviour of strategic agents (*left*, including that of TFT agents), for scenarios involving an initial rate of 90% of D-strategists, with *stochastic* strategy review and F calculated across agents in the *settlement* that share the *same strategy*.



(a) $F \sim U, T = 8$

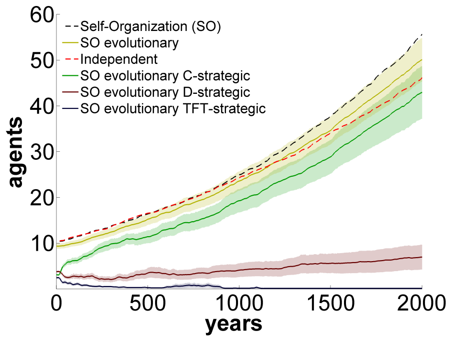


(b) $F \sim U, T = 8$

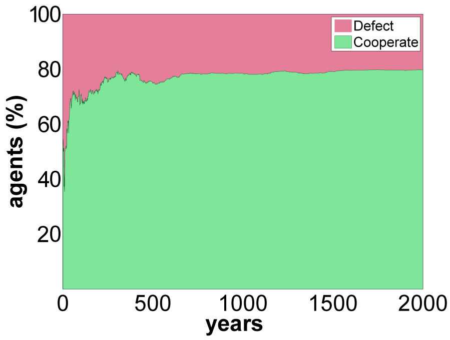


(c) $F \sim R, T = 8$

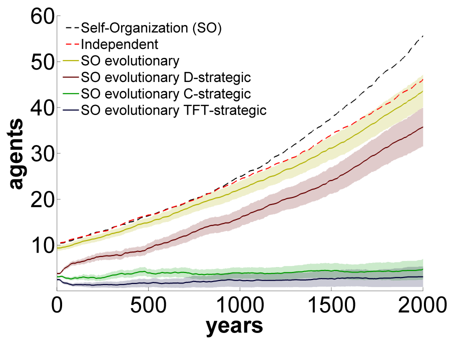
(d) $F \sim R, T = 8$



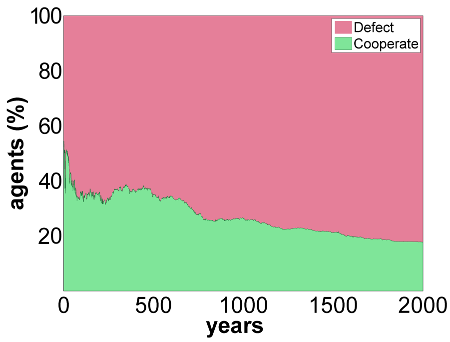
(e) $F \sim U, T = 16$



(f) $F \sim U, T = 16$



(g) $F \sim R, T = 16$



(h) $F \sim R, T = 16$

Figure B.4: Agent population (*right*) and percentage of average cooperative and defective behaviour of strategic agents (*left*, including that of TFT agents), with 20% *error rate* on action selection for scenarios with *stochastic* strategy review and F calculated across agents in the *settlement* that share the *same strategy*.

Appendix C

Additional Simulation Results for Chapter 6

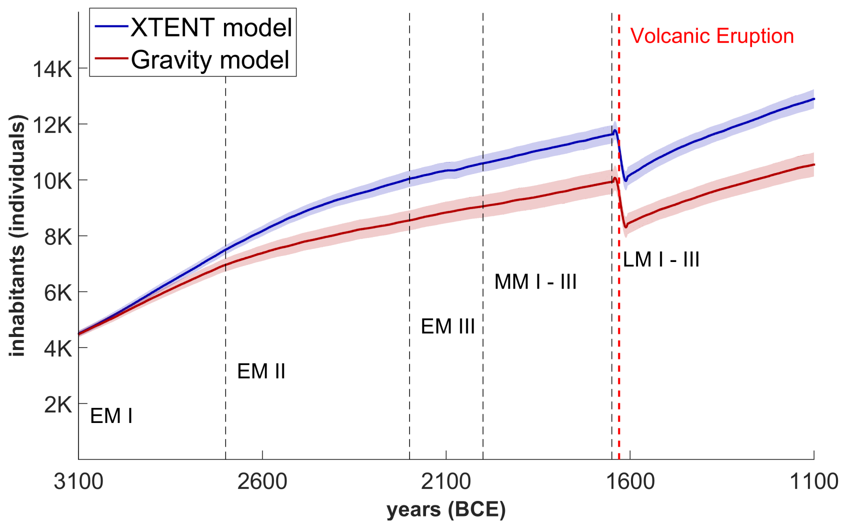
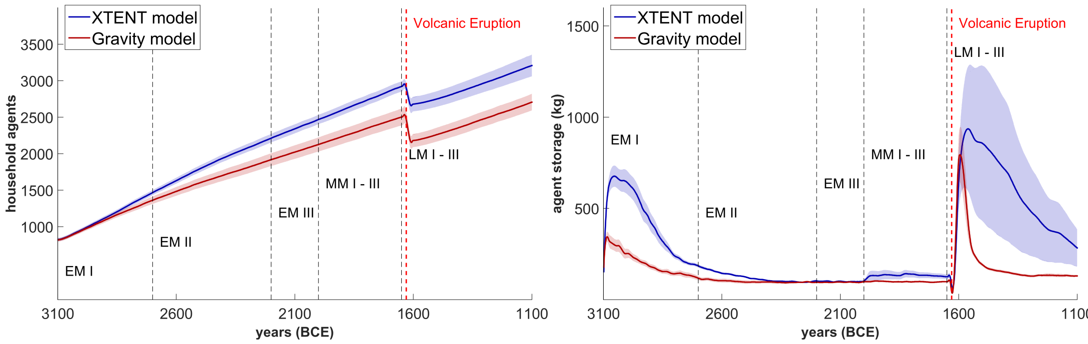
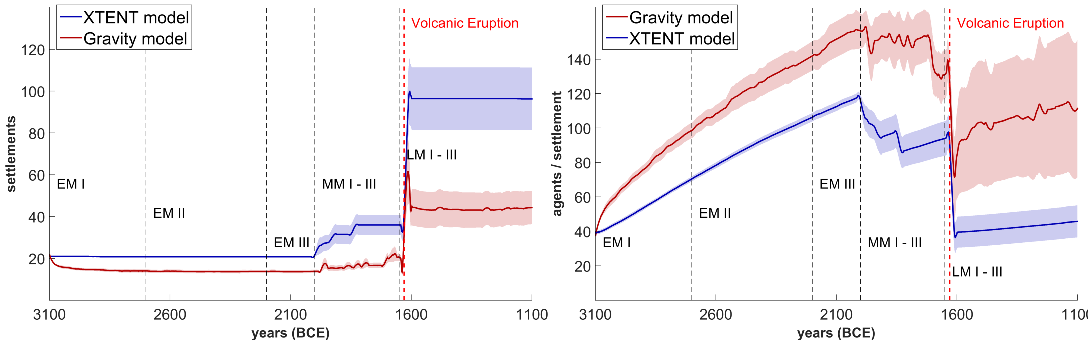


Figure C.1: Population sizes over 2,000 yearly time steps (Minoan period), considering the XTENT and Gravity spatial interaction models, with a lower percentage (20%) of stored surplus trading scheme.



(a) (b)

Figure C.2: (*a*) Population and (*b*) average storage of household agents over 2,000 yearly time steps (Minoan period), considering the XTENT and Gravity spatial interaction models, with a higher percentage (80%) of stored surplus trading scheme.



(a) (b)

Figure C.3: (*a*) Number of settlements and (*b*) settlements size over 2,000 yearly time steps (Minoan period), considering the XTENT and Gravity spatial interaction models, with a higher percentage (80%) of stored surplus trading scheme.

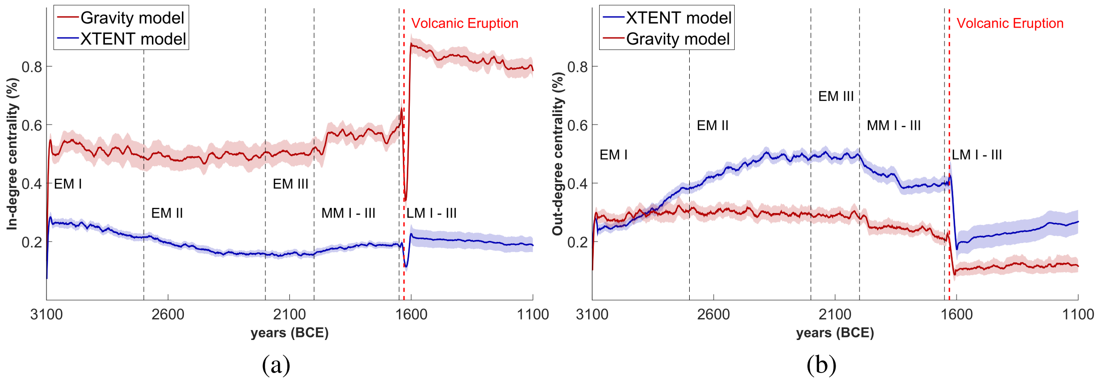


Figure C.4: (*a*) Relative in-degree and (*b*) relative out-degree graph centrality indices of the trading network over 2,000 years (Minoan period), considering the XTENT and Gravity spatial interaction models, with a higher percentage (80%) of stored surplus trading scheme.

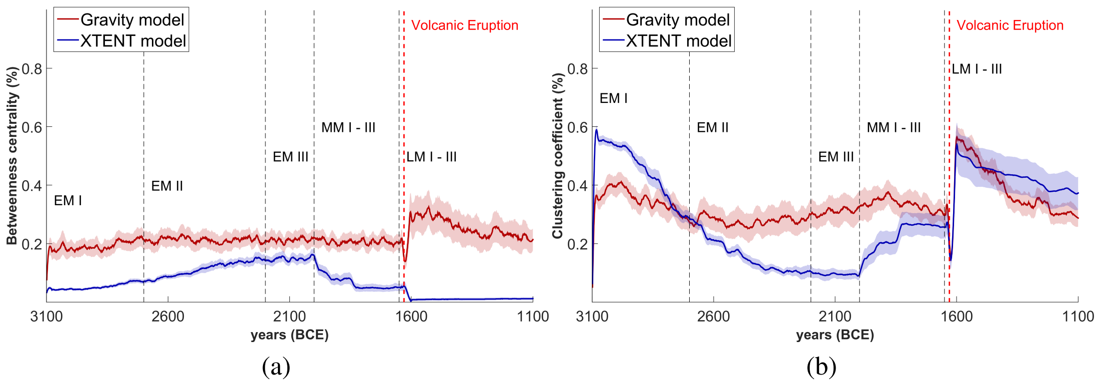


Figure C.5: (*a*) Relative betweenness graph centrality and (*b*) average clustering coefficient of the trading network over 2,000 years (Minoan period), considering the XTENT and Gravity spatial interaction models, with a higher percentage (80%) of stored surplus trading scheme.

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