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PREDICTING THE PAST: SUBSISTENCE, ORGANISATION, AND SURVIVAL OF EARLY AGROPASTORAL COMMUNITIES

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Abstract

This thesis investigates the impact of the environment on the socioeconomic organisation and subsistence strategies of early agropastoral communities. The development and adoption of agropastoralism transformed the way in which communities related to their landscape, adopting new strategies such as sedentarism, animal husbandry or agriculture. Traditional interpretations in archaeology argued that early agropastoral groups located in optimal locations for farming. However, archaeological evidence indicates that there are agropastoral communities settled in different ecological niches despite consuming the same resources, while others consume different resources despite being located in similar niches. To address this question, the Niche Construction Theory approach deals with the relevance of the agency of agropastoral groups to modify their landscape, underlining the importance of other variables related to the social organisation of people in addition to environmental characteristics.

To approach this, a machine learning model based on Bayesian Networks, learned from information extracted from cross-cultural ethnographical societies, has been built to quantify the relationship between a large number of variables that could have shaped agropastoral lifestyle. Additionally, it was possible to make predictions using our learned model, so we were able to predict potential scenarios to explain the configuration of agropastoral communities. One of the main contributions of this thesis is the exploration and quantification of modelling complex agropastoral systems using a machine learning model. Whilst machine learning has gained popularity in other fields of archaeology, it is still uncommon for studying socioecological systems. Furthermore, this work represents the first application of Bayesian networks in socioecological modelling, to the best of our knowledge.

This research emphasises the importance of the coevolutionary process between the environment and agropastoral communities in shaping their settlement location, economic behaviour, and social preferences. In contrast to social groups that relied solely on hunting, gathering or fishing, human communities with mixed farming economies were more diverse, and therefore less constrained by individual factors for particular means of living and working. More variables need to be considered, not just the landscape and environment, to understand how survival was possible thousands of years ago.

By developing a script for building Bayesian networks and sharing the process in open access, we aim to disseminate the application of this methodology to investigate other archaeological contexts. This research is aligned with the current flourishing of computational methods in archaeology, and this thesis hopes to foster a dialogue concerning their integration into the archaeological skill set, and discussion about their strengths, potentials and limitations for modelling socioecological questions.

Keywords: Socioeconomic organisation, subsistence strategies, agropastoral communities, Bayesian Networks, Niche Construction Theory.

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Scientific Terms

Common name	Scientific name
Acorn	*Quercus Fagaceae*
Auroch	*Bos primigenius*
Barley	*Hordeum vulgare*
Bitter vetch	*Vicia ervilia*
Blackberry	*Rubus allegheniensis*
Boar	*Sus scrofa*
Bog pine	*Pinus uncinata*
Burnet	*Sanguisorba officinalis*
Cattle	*Bos taurus*
Chickpea	*Cicer arietinum*
Common vetch	*Vicia sativa*
Cormorant	*Microcarbo melanoleucos*
Dock	*Rumex obtusifolius*
Einkorn	*Triticum monococcum subsp. Monococcum*
Emmer	*Triticum turgidum subsp. Dicoccum*
European pond turtle	*Emys orbicularis*
Fava Bean	*Vicia faba*
Flax	*Linum usitatissimum*
Goat	*Capra aegagrus hircus*
Grape	*Vitis vinifera*
Grass Pea	*Lathyrus sativus*
Hazelnut	*Corylus avellana*
Holm oak	*Quercus ilex*
Iberian wild goat	*Capra pyrenaica*
Juniper	*Juniperus*
Lentil	*Lens culinaris*
Lotus	*Nelumbo nucifera*
Lynx	*Lynx pardinus*
Mint	*Mentha*
Oak grove	*Quercus agrifolia*
Pea	*Pisum sativum*
Pig	*Sus domesticus*
Poppy	*Papaver somniferum L.*

Common name	**Scientific name**
Rabbit	*Oryctolagus cuniculus*
Red deer	*Cervus elaphus*
Red elderberry	*Sambucus racemosa*
Red fox	*Vulpes vulpes*
Ribwort plantain	*Plantago lanceolata*
Roar deer	*Cervus elaphus*
Rose	*Rosaceae*
Rye	*Secale cereale*
Sheep	*Ovis aries*
Sorrel	*Rumex acetosa*
Swinecress	*Lepidium didymum*
Wild cherry	*Prunus avium*
Wildcat	*Felis silvestris*
Wolf	*Canis lupus*
Woodcock	*Scolopax rusticola*

Abbreviations

ABM	Agent-based model
AI	Artificial intelligence
BN	Bayesian networks
BSR	Broad-Spectrum Revolution
CDM	Cultural Diffusion Model
CET	Cultural Evolutionary Theory
CNCT	Cultural Niche Construction Theory
CPT	Conditional Probability Table
CST	Complex Systems Theory
DDM	Demic Diffusion Model
EDA	Exploratory Data Analysis
EET	Ecological Evolutionary Theory
FOSS	Free of charge and Open-Source Software
GIS	Geographical Information System
GRASS	Geographic Resource Analysis Support System
HBE	Human Behavioural Ecology
KIDS	Keep It Descriptive, Stupid
KISS	Keep It Simple, Stupid
ML	Machine learning
NCT	Niche Construction Theory
ODD	Overview, Design concepts and Details
OFT	Optimal Foraging Theory
PPNA	Pre-pottery Neolithic A
PPNB	Pre-pottery Neolithic B
RL	Reinforcement learning
SA	Sensitivity analysis
SES	Socio-Ecological Systems theory

Introduction

I. Research Topic and Objectives

Agropastoralism is a livelihood system that integrates crop and livestock production. Agropastoral societies have a mixed economy in which at least 50% of their diet is based on agriculture and animal husbandry. Human groups also rely on foraging subsistence strategies such as fishing, gathering, and hunting. Therefore, it is implicit that societies control the breeding, growing and production of the consumed resources, which is why agropastoral communities tend to be located in areas/regions that meet their production needs. The produced resources vary greatly depending on climate, culture, topography, and water availability, *inter alia*.

In Prehistory, agropastoralism tends to be associated with sedentarism but this is not always the case. In fact, this traditional view is gradually changing with the improvement in archaeological practices in the identification of temporary settlements, transhumance practices in mountainous landscapes, and different intensities of food production and consumption. This variety is also evidenced in current agropastoral groups as some may be sedentary, semi-sedentary, or mobile. Diversity has often been misrepresented in research on early Neolithic communities as they tend to assume that early agropastoral groups were sedentary, located in optimal places for farming. But this representation of agropastoralism is generally not supported by the archaeological evidence.

Consequently, an increasing number of research studies are addressing this gap, exploring the importance of this diversity in lifeways during the early Neolithic to gain further understanding of how and why these communities lived in the way they did. For this, a crucial element that has been pointed out since the blooming of the **Niche Construction Theory** (Laland et al., 1996, 1999; Odling-Smee et al., 1996), is the influence of the landscape features for defining **human agency**. In this work, we have followed Sen's definition of human agency (1979, 1985) which considers to be the ability of people to act on behalf of goals that matter to them, so they can shape their destiny and not just act as passive agents. Agency can be exercised at the individual level or in groups but, in this work, we will generally consider this concept at the collective-level due to the difficulty of identifying individuality in the archaeological record.

The way of conceptualising the relationship between the actions of past communities and the landscape characteristics has changed profoundly in recent times. Part of this change has been due to technological developments to characterise variables with greater precision (e.g., soil productivity), and to develop computational methods to process this evidence. Statistical, simulation, spatial and machine learning models are currently employed to quantify empirical evidence and experiment *in silico* (computationally) to better understand the relationship between landscape and human agency. It is no longer considered that the survival of early agropastoral communities was defined by the availability of resources, as people was also able to modify the surrounding social and environmental landscape to meet their needs. Three potential mechanisms can be suggested from the archaeological record: (i) modifying the intensities of food consumed (diversification of different resources, intensification of particular resources), (ii) their social relationships (exchange, reciprocity) or overcoming environmental limitations (transhumance, migration). This makes the modelling of early agropastoral communities a more complex and complicated task.

Defining what mechanisms were employed in prehistoric times is challenging. For this reason, **predictive modelling** is suggested for 'filling the gaps'. Prediction can be described as a statement about some outcome(s) that is(are) expected. The *effect* can be predicted when the *cause* and the *mechanism* is known. Predictive modelling employs statistical methods for predicting the most probable effect from all the potential causes. To do such prediction, it is necessary to know prior cases to measure the probabilities given all the possibilities.

Archaeologists usually intend to predict what people did in the past from the actual material evidence produced by the people living there and then. Predicting the past entails discovering what happened many years ago from the material evidence generated at that time and preserved until today. In case we know the **input** – archaeological and paleoenvironmental data describing a particular scenario- and the **mechanisms** – socioeconomic activities performed by people, we will be able to solve the problem, the **ouput** – whether people survived once at that area. However, in too many cases, we do not know what socioeconomic activities occurred. We may have some material evidence but not the mechanism, the particular action. There is the additional difficulty that there is not a single trace that may unambiguously discriminate one activity from others. We can, however, predict the 'most probable' given all the possibilities.

In this context, machine learning models represent a good option to investigate this topic. Unknown data can be predicted using such a model learned from a training dataset, which is a crucial advantage as data is fragmented or partially preserved. In addition, this methodology deals with large datasets and designs and quantifies the relationships between multiple variables. In machine learning, there are predictive algorithms, such as neural network, which are the most common in archaeological research. However, they have the disadvantage of being a 'black-box', which means that the calculations made by the model to transform the evidence about the input variables into the predictions for the outputs, are not visible. As a result, the modeller only knows the training data used to learn the model and the output. Not all machine learning methods have this limitation. In this study, we will focus on **Bayesian networks**, a 'white-box' probabilistic algorithm.

Despite Bayesian networks have proven to be a suitable predictive model, they are still uncommon in archaeological studies. Before this thesis, there was no previous application in archaeology of Bayesian networks and, consequently, there was no prior study in archaeology introducing this machine learning method that defined its characteristics, applications, or guidelines for its construction. This thesis aims to fill this gap and explore the suitability of this methodology to explore a specific topic, such as the relationship between the landscape, the mechanisms to ensure survival and subsistence strategies of early agropastoral communities. We will do so through the following research objectives:

OBJECTIVE 1. Assess the suitability of Bayesian networks for modelling past socioecological systems

OBJECTIVE 2. Explore ways of quantifying the probable impact of environmental features on prehistoric social behaviour, even when this impact may have been indirect

OBJECTIVE 3. Analyse the probability of social behaviour depending on different socio-natural contexts

OBJECTIVE 4. Investigate the social and economic dynamics of early agropastoral systems, how economic decisions may have affected chances of survival in the prehistoric past, and its consequences on the likelihood of finding enough archaeological evidence for a proper historical explanation

These objectives are aligned with current archaeological research studies exploring the human agency of early agropastoral communities employing computational methods. We believe that this thesis will bring new information on our understanding of how these groups ensured their long-term survival in different landscapes. Additionally, we hope that by discussing the current computational methods used to explore this topic and our application with Bayesian networks, we will encourage a debate about the importance of these methods in archaeology, their potentialities, limitations, and how they can be integrated with other computational methods.

II. Thesis Structure

This thesis is structured in four chapters. **Chapter 1** presents current theoretical and methodological approaches to investigate the relationship between early agropastoral groups and environmental characteristics. The Niche Construction Theory is defined as the theoretical framework followed, and Bayesian networks are introduced as the methodology applied. The current state-of-the-art of computational methods to model prehistoric systems and some of the most representative models developed thus far are presented. Bayesian networks are introduced and compared with other machine learning models. The research paper '**Palacios, O.** (2023). Aplicación del aprendizaje automático en Arqueología: ¿Un cambio de paradigma?. *Vegueta. Anuario de la Facultad de Geografía e Historia, 23*(1), 147-186. https://doi.org/10.51349/veg.2023.1.06' is provided at the end of this chapter. This study is a bibliometric analysis of the application of machine learning methods in archaeology, defining which algorithms are the most common and for what purposes they are used.

Then, **Chapter 2** deals with two major periods of change that have been associated with the environment: the development and adoption of agropastoralism in Southwest Asia, and its expansion across the Mediterranean. It is divided into two sections, each of which focuses on a period of change. In each section, empirical archaeological evidence of what happened, where, and when is provided first, followed by models that have been previously developed to explain why and how. At the end of Chapter 2, it is included the book chapter 'Barceló, J.A. & **Palacios, O**. (2023). Computational simulation of prehistoric migrations. Western Mediterranean Early Neolithic case study. In V. Heyd & M. Ahola (Eds.), Moving and Migrating in Prehistoric Europe. London: Springer Routledge', which investigates in more detail what sort of variables should be considered for modelling the expansion process.

Chapter 3 presents the current evidence of early agropastoral communities in the Iberian Peninsula. The heterogeneity of the archaeological record which evidences that both Mesolithic and Neolithic communities inhabited different ecological niches and for long period of times is discussed, questioning the traditional dichotomy between both groups. To investigate the influence of the landscape on agropastoral communities, two research papers have been developed to explore this question: '**Palacios, O.**, Barceló, J.A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. *Plos one*, *17*(10), e0276088. https://doi.org/10.1371/journal.pone.0276088', and '**Palacios, O.** & Barceló, J.A. (2023). Survival in prehistory: Disentangling the complexity of dependent relationships. *Journal of Anthropological Archaeology'*. The first research paper focuses on the methodology for the construction of a predictive model based on Bayesian networks and the main results obtained. The second paper deals with the importance of social agency and behaviour and its impact on the survival of these communities.

Chapter 4 concludes this thesis by reviweing the main topics presented in each chapter, thus contextualising the major contributions made of this thesis. The principal results are exposed along with potential future research directions.

Chapter 1
Computational Methods to Understand the Past

1.1. Human Behaviour and Landscape

Until the last mid-century, with the **Evolutionary Theory** (Dunnell, 1979, 1980, 1989), the general idea was the environment determined the possibility of survival of agropastoral communities. That is, people would have never lived in regions with poor soil and weather conditions as all communities would have aimed for the best-suited lands for carrying out farming and animal harvesting. From this approach, two different lines of research emerged: the **Cultural Evolutionary Theory** (CET) (Cavalli-Sforza & Feldman, 1981; Boyd & Richerson, 1988) and the **Ecological Evolutionary Theory** (EET) (Lenski, 2015).

The CET highlighted the importance of considering people's agency for deciding and modifying their economic activities, ecological conditions, and social interactions. This introduction was associated with a change of mind on Neolithic communities' representation: instead of assigning a passive role, they were studied as active agents that made their own decisions depending on their interests, preferences, and needs (and not only influenced by the environment of their site, for example).

Conversely, other researchers placed more importance on the role of ecology for modelling socioeconomic activities of people in the past. In this line, the EET argued that past people were influenced by the ecological context, and they had to adapt and changed the way they organised, ate, lived, to adapt to the circumstances. This approach, therefore, implied that past communities did not have any specific goal or preferences but adapted to the environmental context. They lived in habitats with specific *niches*, available resources and *carrying capacities,* the maximum measure for supporting the humans and animal species living in that location.

Considering these concepts, the starting point of this approach was the optimisation hypothesis, which assumed that people always exploit the habitat in a rational way, minimising their effort to satisfy their needs. This premise led to the conceptualisation of the **Optimal Foraging Theory** (OFT), developed by MacArthur and Pianka (1966) and introduced in archaeology by Winterhalder and Smith (1981). This theory was mainly based on the simple model of predator and prey interactions, named the *Lotka-Volterra Model* (Lotka, 1925; Volterra, 1926) which was based in nonlinear differential equations modelling the interaction of two species (the prey and the predator). The main assumption of this model was that prey populations always find food; the food supply of the predator is only based on the prey population or that the rate of change of population is proportional to its size. Based on the same principles, this theory was applied to model communities that based their subsistence on hunting-gathering-fishing activities (henceforth foragers). When food was encountered (prey), foragers (predators) would have balanced the costs of acquiring, processing, and transporting the prey with the benefits, which would have been the acquired energy. The difference between the costs and benefits it is what would have determined if pursuing or not the prey.

But did foragers count calories and hours? Since its conceptualisation, the principal critique of this model was the use of modern capitalist economy such as individualism (probably not only one person conducted all the activities), but self-interest also (if it compensated the time and energy spent), or maximisation (obtaining the maximum benefits with the less time invested). Not so far away in time and space, we have numerous examples of agropastoral communities that, mostly due to the climate change and governmental policies, they must invest more time and effort in obtaining the food than the energy and money spent (e.g., Homewood et al., 2019; Ifejika Speranza, 2010). To cope with this difference, such communities have acquired multiple strategies although they could migrate permanently to bigger cities to ensure their long-term but instead, they stay in 'less optimal' locations (e.g., Ravera et al., 2011; Bollig, 2006). The reason why they acquire new subsistence strategies is clear, to survive, but the reason why they do not move out comes down to personal, domestic, community preferences that are hardly measurable.

There are currently two principal theoretical frameworks in archaeology, the **Human Behavioural Ecology** (HBE) and the **Niche Construction Theory** (NCT), both branches of evolutionary theory. The HBE was developed in mid-70s (e.g., Denham, 1971; Dyson-Hudson & Smith, 1978; Wilmsen, 1973) to study socioecological responses of animals (applied to humans in archaeology) in facing constraints (e.g., food scarcity, climate change). From this approach, the most effective response is the one selected as being the most probable (following the OFT). Most studies applying HBE in archaeology deal with the foraging theory (especially the diet breath model) or resource distribution (Cannon & Broughton, 2010; Nettle, 2009; Kaplan et al., 2005). Conversely, NCT, developed in mid-90s (Laland et al., 1996, 1999; Odling-Smee et al., 1996), focuses on the impact of the behaviour on the environment from the premise that human actions modify the landscape. In this sense, unlike the HBE, it considers the dynamism and co-evolutionary transformations resulting from human - environment relationships (Odling-Smee et al., 2003; Laland et al., 2001; Laland & O'Brien, 2010; O'Brien & Laland, 2012). Another divergence is that NCT does not take into account the most effective behaviour since niche construction can affect negatively to fitness. Whilst the HBE has a rooted tradition of application in forager studies, the NCT is commonly applied to explore the origins of agropastoralism (e.g., Bogaard et al., 2021; Abbo & Gopher, 2020). Despite these differences, there is a vibrant debate about the potential complementarity of these two frameworks (e.g., Gremillion, 2019; Zeder, 2015).

Since the NCT explores the decisions and preferences of past people, the concept of culture, understood as a non-genetic inheritance process socially transmitted, plays a crucial role. For this reason, there is the variation of this framework that explores specifically the impact of culture, known as Cultural Niche Construction Theory (CNCT) (Smith, 2011; Zeder, 2016). It argues that humans can actively modify the environment with previously learned behaviours that to ensure their long-term survival. This goal-oriented approach of NCT has been strongly criticised by some authors for being vague in conceptualisation (Spengler, 2021) and considered a 'manufactured subdiscipline within the scientific community' (Gupta et al., 2017:491) that already existed.

1.2. Systems Modelling, Behaviour Prediction

1.2.1. Inferring the Past

To investigate the relationship between social actions of the past and the environment in which communities lived, produced, and consumed food resources, we need to re-create the past. We may never re-create faithfully the past, but that recreation may provide us with further insights into where, when, how, and why systems lived in that way in the past. Our goal should be to 'reverse' the past, observe the empirical evidence and 'reconstruct' its production process and context. This approach has been called '*reverse engineering'* and defined as the study of a sample of a product, device, or machine, to discover how it functions or has been made (Raja & Fernandes, 2008; Messler & Faws, 2014; Camagni et al., 2019). Thus, it is a type of backward inference from the end state to the beginning state of some system. With reverse engineering, the researcher starts the final product -the empirical archaeological evidence- and works through the design process in the opposite direction of the formation process to arrive at the original product -past communities-. That is, given a particular state within a determined design system, we should infer the previous state by *reconstructing* the mechanism that produced the observed deformation. The problem to solve is equivalent to what philosophers of science refer as an *inverse problem*: we see the *effect*, and we want to infer the *cause* (Pizlo, 2001; Bunge, 2017; Gelman & Imbens, 2013). Following this idea, archaeology has been described as an 'inverse science', in which 'we can see the effect but the causes and/or motivations ('the social dimension') are unknown (unobservable)' (Barceló, 2017:23).

To reconstruct the **mechanism**, we need to model the reality that we want to explore. Models are representations of a selected part or aspect of the reality that we want to investigate (Frigg & Nguyen, 2017). To produce models, there are two principal approaches: *deduction* and *induction*.

Deduction is a top-down approach that examines the available data (top) to deduce patterns or structures (down) that can inform us concerning the behavioural practices in the past, for example. In other words, deduction reasons from the premises to reach a logically certain conclusion (Coccia, 2018:119). It is a well-suited method in archaeology for its capacity to extract mechanisms from partially preserved empirical evidence, but it has the disadvantage of always considering 'true' the deductions and validation limitations.

Induction, on the other hand, is a bottom-up approach that derives theories from the data (bottom) to extract the mechanisms (up) (Gärdenfors & Stephens 2018; Barker, 2020). Therefore, results obtain with induction are expressed in terms of probabilities. When the research questions require some sort of data that cannot be quantified with the archaeological evidence (e.g., manufacture processes, use of technologies) or for results validation, experimental archaeology is a suitable method (O'Neill & O'Sullivan, 2019; Paardekooper, 2019; Lammers-Keijsers, 2005). It employs induction to bring together the past evidence and the social evidence. Induction represents one of the most fundamental notions for archaeological inference is that of similarity: the solutions to an archaeological problem group together things that are similar. Two entities are similar because they have many properties in common. Similarity depends on the context in which they occur, but two different things can be present in the same context. For instance, a community may hunt less if it relies heavily on farming but, hunting may also be a minor activity when communities live in the coast. Thus, in this case, the intensity of hunting may be related to the intensity in which farming is practised and/or the location. But location and farming may not be related and, consequently, have an independent relationship.

Modelling past communities is, therefore, not only complicated because we need to consider many variables that may have shaped their lifestyle, but also *complex* because these variables were interrelated in a dynamic involving decision-making by individual/community's perception on their social and environmental landscape. To include all these variables and introduce the complexity among different variables in SES, the **Complex Systems Theory** (CST) (initially known as 'General Systems Theory' by Von Bertalanffy, 1950) was incorporated in archaeology. The fundamentals of this approach were formulated as follows:

> "*There exist models, principles and laws that apply to generalised systems or their subclasses irrespective of their particular kind, the nature of the component elements, and the relations or*

'forces' between them. We postulate a new discipline called General Systems Theory. General Systems Theory is a logic-mathematical field whose task is the formulation and derivation of those general principles that are applicable to 'systems' in general. In this way, exact formulations of terms such as wholeness and sum, differentiation, progressive mechanization, centralisation, hierarchical order, finality and equifinality, etc., become possible, terms which occur in all sciences dealing with 'systems' and imply their logical homology" (Von Bertalanffy, 1950).

The underlying assumption is that systems could be studied by identifying their variables, which can be **inputs** (parameters, initial conditions, assumptions, constraints) and **outputs** (the model responses, what we aim to predict), and **mechanisms** to organise the range of behaviours present in the system (Mitchell, 2009). This new conceptualisation represented a crucial change to investigate past systems by providing dynamism to the relationship between the environment and past communities (Kohler & Van der Leeuw, 2007), where the archaeological record was considered the sum of numerous activities dilated in time (e.g., what they produced, consumed, interactions among people, used artefacts, etc.). Only by looking at the biased materiality (the archaeological record) would not be feasible to comprehend the social, economic, and ideological landscape of the past system. Leaving behind the positivism of the New Archaeology, CST proposed a framework of doing a more 'global' archaeology, less centred in specific cases (Carmichael & Hadzikadic, 2019). In words of Schlüter et al. (2017), 'it opened up the possibility of investigating general social-cultural concepts like worldviews, collective traditions and experiences, beliefs, or attitudes'.

In this line, SES are defined from a system-based perspective that looks at the behaviours and interactions between social (e.g., subsistence strategies, transaction mechanisms, mobility) and ecological (e.g., climate, soil characteristics, topography) components (Berkes et al., 2000). They are inherently complex systems as their interactions are the result of complex, dynamics, and interconnected structures with feedback across socioenvironmental dimensions (Ferraro et al., 2019). For this reason, the principal way of modelling them is through computation.

1.2.2. Model Construction

Computational modelling is not new in archaeology. The first computational model in social sciences was the 'Segregation model' (Schelling, 1969) to model the ethnic distribution patterns of neighbourhoods. In 1970, the 'Game of Life' (Conway, 1970) was designed, representing the emergence and auto-organisation of cells. These ideas of modelling behavioural dynamics were adopted by archaeologists following the Evolutionary Theory (some examples are Doran, 1970; Flannery, 1972; Wobst, 1974; Cooke & Renfrew, 1979). From early applications until today, many different computational models with different characteristics have been developed in connection with advances in the archaeological knowledge and technology (for an overview of computational trends in archaeology see Lake, 2014). Among the strengths of computational modelling, their use for *data mining* (explore data and develop new hypotheses), and *explanatory capacity* of complex systems represent the most relevant applications in the archaeological field.

The building process of all computational models is rather similar as there are attempts by the archaeological community to improve the transparency and reproducibility of the models. In general, the building process encompasses four steps: conceptualisation, model design and experimentation, validation, and dissemination.

Step 1. Conceptualisation*:* determine as precise as possible the question that the models aim to answer and choose the most suitable approach. There are two types of models: (i) *Phenomena-based* (known as explicit models) aims to understand the mechanisms that cause the observed pattern (e.g., why communities abandoned a settlement); (ii) *Exploratory* (known as hypothetical models) tend to be more abstract as are designed to explore whether patterns or any aspect of interest emerge with defined actions (e.g., the effects of intensive farming in a settlement).

Step 2. Model design and experimentation*:* there are two options to design the model, in the *top-down approach* the modeller designs the agents, interaction rules and environment before writing the code. Conversely, in the *bottom-up approach* the model's conceptualisation and the code are defined simultaneously, influencing the elaboration of the other. Despite this difference, most modellers combine both approaches as the model conceptualisation tends to vary during the building process. Concerning what variables include in the model, there are also two main approaches: the KISS (Keep It Simple, Stupid) and the KIDS (Keep It Descriptive, Stupid). As the names depict, the former approach supports modelling the minimum of entities and processes as possible to simplify the model whereas the other approach argues for a detailed model to then eliminate those variables that turn out to not be significant. By forcing to specify the elements of our arguments, such as actors and their goals, modelling should increase clarity and explicitness, reducing ambiguity and vagueness. There is a wide range of different open-access software to implement computational models, being the statistical software R the preferred choice (R Core Team, 2022).

Once the model is built, a common step is to conduct an Exploratory Data Analysis (EDA) using statistical techniques like correlation or regression techniques in combination with data visualization methods. EDA is used to spot problems in the model and to obtain a general overview of the model and identify those features that may be interesting to explore in detail. In case of any anomaly is identified, the model needs to be mended and conduct EDA again. When the model is prepared, results are generally obtained using two methods: parameter sweep and alternative testing. In parameter sweep, the modeller modifies all parameter values gradually with the aim to identify potential dependencies among parameters, thresholds, and feedback loops (Romanowska, 2015). Alternative testing, on the other hand, consists of designing different simulation scenarios that aim to explore different questions so patterns and interesting insights can be obtained.

Step 3. Sensitivity analysis (SA)*:* is used to examine the robustness of results obtained in the model by exploring how the outputs are influenced by the inputs (Razavi et al., 2021). To conduct the SA, one parameter at a time is changed while the rest remain the same so the modeller can identify potential effects of that parameter on the results. Usually, this process is conducted changing various parameters, so patterns and relations are observed. In this sense, a *robust* model is the one when the output values of interest remain within the defined interval (Chattoe et al., 2000). During this examination, three different goals can be achieved: (i) make a scientific discovery as the hypotheses, scales, and interactions of the system (e.g., Gupta & Razavi, 2018), (ii) identify potential processes and parameters that dominantly control the system, (iii) quantify the reliability of the data and results obtained.

As noted by some researchers (e.g., Chattoe et al., 2000; Kanters et al., 2021), models built in social sciences and particularly archaeology, do not tend to perform SA and publish the experiments process. Consequently, it is difficult for the other researchers to assess the robustness of the model and reuse. For agent-based modelling, the MERCURY model (Kanters et al., 2021) was designed to achieve this aim but, besides this initiative, there have not been more attempts to address this issue.

Step 4. Dissemination*: s*ustainability and reusability have become relevant factors to consider in archaeology. Instead of building a model to explore a specific context, it is increasingly becoming more common to design models that can be reused to investigate different contexts and periods and publish them in open-access, following the FOSS principle (Free of charge and Open-Source Software). To ensure this, practices such as standardization retrieved data, data sharing, open data and recycling are crucial factors to ensure a more sustainable archaeology. In this line, open software such as R (R Core Team, 2022) or NetLogo (Wilensky, 1999) are encouraged since they can be reused and improved by the research community.

1.2.3. Types of Models

In general terms, there are three principal categories of computational systems in archaeology: **GIS-based**, **Agent-based** and **Machine learning modelling** (Brower Burg et al., 2016).

GIS-based modelling is characterised for being highly detailed in geographic, geologic, vegetation, and faunal context where the human action takes place. To build accurate reconstruction of paleolandscapes, powerful geographic information system software such as ArcGIS (Redlands, 2011), QGIS (QGIS organisation, 2023) or GRASS (GRASS Development Team, 2022) are used. Some examples of this modelling applied to explore SES questions include Ullah et al., 2019, or Sikk et al., 2022.

The principal strength of GIS-based modelling (Geographical Information System) is the production of detailed and accurate palaeoecological models which can be used as foundation for modelling unpredictable behaviour of human agents. On the other hand, the main disadvantage of using this kind of modelling for exploring archaeological question is the lack of sufficient or reliable environmental data as obtaining a detailed landscape of past systems is challenging. The resulting landscape is a static map surface instead of reconstructing dynamic models. Another limitation of this approach is the type of models that are usually produced: they are mostly focused on specific regions and short time span rather than investigating broad-level trends that could be applicable in diverse spatiotemporal contexts (Brouwer Burg, 2016).

Since the development of the first **Agent-based model** (ABM) of social sciences, the 'Sugarscape' (Epstein & Axtell, 1996), which represented the carrying capacity of resources in an artificial environment, this method has gained relevant importance for conceptualising the social dimension in archaeology (for further details, see Romanowska et al., 2021). It attempts to explain macro-scale behavioural phenomenon through high volume iterations of socioecological dynamics. It is broadly used to investigate SES due to its capacity for experimenting with the systems *in silico* in geographical accurate settings, as it can be coupled with other software such as GIS or GRASS (Geographic Resource Analysis Support System). The model can be implemented using specific software such as NetLogo (Wilensky, 1999), Cormas (Bommel et al., 2016), MASON (Luke et al., 2019) or Repast (Collier et al., 2003). Consequently, it is possible to create virtual worlds in which socio-ecological dynamics can be studied at temporal and spatial scales not possible in real-world contexts (Barton et al., 2012:51).

The principal critique to ABM concerns its validation difficulties: if empirical data is used for building and validating the model, results will always match initial assumptions (for a detailed description of the limitations see Epstein, 2012; Kohler & Gumerman, 2000). However, a considerable effort has been made to address this problem, by building accurate protocols for model building and validation such as the ODD (Overview, Design concepts and Details) protocol (Grimm et al., 2010, 2020) or the TRACE (Schmolke et al., 2010; Grimm et al., 2014) and the code publication in online repositories like the CoMSES Computational Model Library (CoMSES Net, 2023), or GitHub. Additionally, in recent years, more former guides have been published to make more accessible the knowledge and necessary training of ABM to archaeologists that want to learn this method (see the step-by-step volumes of Romanowska et al., 2019, 2021; Davies et al., 2019; Crabtree et al., 2019).

The constant revaluation of protocol, quality and transparency of agent-based models have placed this kind of computer model as one of the most widespread methods in archaeology. It has been employed for exploring a wide range of different decision-making processes such as management policy (Cioffi-Revilla, 2002), power emergence (Kohler et al., 2012; Rogers, 2017), exchange (Bentley et al., 2005; Kobti, 2012), inter-agent social learning (Kohler et al., 2012; Mithen, 1988; Premo & Scholnick, 2011), subsistence procurement (Gravel-Miguel et al., 2022). Particularly developed for modelling SES, there are four crucial models that have defined this line of research: the *Village Ecodynamics* (Kohler et al., 2005, 2007; Ortman et al., 2007; Odum & Barrett, 2005; Kohler & Reese, 2014; Kohler et al., 2012), *WELASSIMO* (Baum, 2014, 2016; Baum et al., 2016, 2020), *ENKIMDU* (Altaweel, 2008; Wilkinson et al., 2007; Christiansen & Altaweel, 2006), *The Mediterranean Landscape Project* (Barton et al., 2010, 2012; Ullah & Bergin, 2012; Barton, 2016; Bernabeu Aubán et al., 2003; Mayer & Sarjoughian, 2009). Their differences are described in **Table 1**.

Model	The Village Ecodynamics	WELASSIMO	ENKIMDU	The Mediterranean Landscape project
Software	NetLogo	NetLogo	Java and implemented with DIAS (Dynamic Information Architecture System), FACET (Framework for Addressing Cooperative Extended Transactions) and JeoViewer	Python and implemented with GRASS GIS software (landscape and land-use) and Java-based DEVS-Suite (household consumption)
Objective	Identify why ancient Anasazi Puebloan people abandoned the Long House Valley by 1,2 ka BP	Explore socio-economic dynamics of Neolithic wetland sites through the simulation of crop husbandry yields	Explore agricultural sustainable of agropastoral settlements of ancient Mesopotamia	Investigate the consequences of rural land-use practices in the Mediterranean area
Study area	Long House Valley (Mesa Verde National Park, north-eastern Arizona), 7- 1,3 ka BP	Northern pre-Alpine area, 6,2-5,6 ka BP	Northern and southern Assyrian heartland, Ancient Mesopotamia	Mediterranean area (from eastern Spain to western Jordan) in the Holocene
Environmental variables	Topography: elevation, slope, accessibility to rivers (catchment areas and aquifer waters). Soil characteristics: depth, moisture, type, natural plant productivity, agricultural yield Climate: annual and monthly temperature, annual and monthly precipitation	Topography: elevation, slope Soil characteristics: type, yield, productivity, carrying capacity, forest development. Climate: mean temperature and variation, mean precipitation, and variation	Topography: soil evolution, hydrological evapotranspiration, types, nutrient cycling, vegetation growth Climate: wind, temperature, precipitation, sunshine/overcast	Topography: slope, elevation Soil characteristics: type, erosion, thickness, depth, fertility, land cover, flowing water accumulation Climate: temperature and precipitation
Resources	Agriculture: maize Foraging: hunting Others: fuelwood	Agriculture: cereals Animal husbandry: cattle Foraging: hunting, gathering, and fishing Others: timber	Agriculture: barley Animal husbandry: cow, sheep, goat Foraging: fish	Agriculture Animal husbandry Others: fuelwood

Model	The Village Ecodynamics	WELASSIMO	ENKIMDU	The Mediterranean Landscape project
Population size	Nuclear families composed by five individuals: two adults of 17-30 years and three children below 17 years	Settlements are formed by ten households. Each household is a nuclear family composed by an average of six individuals (two adults and children)	Households are composed by six able-bodied individuals (not infants or beyond 65 years)	Individual agents organised in villages
Population behaviour	Households aim to meet their caloric needs with farming, and they make decisions based on past experiences according the OFT (they always follow the most efficient option)			
Mobility	Households practise exchange through reciprocity between other neighbour households and they can also relocate to find a more efficient location	No mobility. Households are resilient and have a flexible diet to overcome scarcity.	Relocation when not enough calories are obtained	Not specified
Conflict and war	The model considers the emergence of leadership, internal warfare, or socio-political instability	Not specified		
Results	The results of the model suggest that socio political or ideological factors may have led the surviving Puebloans to leave the valley	Wetland settlement practised permanent cultivation and scarcity of woodland resources was probably the cause for settlement abandonment	It proved that Neo-Assyrians had a significant impact on the archaeological and ecological landscapes surrounding their capital due to the importance of the cities in contrast to other governed areas	Interesting insights concerning resources management in Mediterranean landscapes were obtained

Table 1. Overview of the principal agent-based models designed for exploring past socioecological systems.

Artificial Intelligence (AI) is a discipline born in the 1960s that encompasses all algorithms that attempt to make a machine imitate the cognitive functions of humans, such as learning or problem solving. **Machine Learning** (ML) is the AI subfield of the algorithms that enable a machine to analyse data, build models that improve (predict better) as they feed on more data, and make predictions with these models, which help to make decisions, and generate knowledge. The ML models are self-learned from a database from which they feed, adapting automatically to its updates. They require complex math and programming to implement the algorithms.

ML has gained relevant importance in archaeological science in recent years. To explore past socioecological systems, ML has been applied to study migration (e.g., Vahdati et al., 2019), socioeconomic resources management (e.g., Ahedo et al., 2019, 2021; Burry et al., 2018; Barceló et al., 2015; Alberti, 2014) and cultural dynamics (e.g., Hyafil & Baumard, 2022). Especially significant is the combination of the use of machine learning with remote sensing (e.g., Argyrou & Agapiou, 2022; Casini et al., 2022) to reduce the time-consuming and economic cost of surveying and excavation. Additionally, a line of research that is becoming increasingly important employing these methods is the preservation of archaeological heritage and risk assessment (De Masi et al., 2021). In the same context, the field of predictive modelling with ML is also growing rapidly (Castiello, 2022).

This increase in applied studies in archaeology has been possible thanks to the alignment of multiple factors: the availability of large open-access datasets, the introduction of coding and computational methods in archaeology, the technological improvement of open easy-to-use software such as R. These factors have allowed archaeologists to learn and implement computational methods to address archaeological problems from different perspectives. In this context, the use machine learning methods has become more common in the last five years. The main reasons for the growing popularity of this methodology are that it makes computational processing feasible and effective (it does not require as much computing power as ABM, for example) and the models have feedback loops (the results predicted by the model are reused to train new versions of the model). Consequently, ML is well-suited for recycling and reusing models since even if the model is built and results are collected, if we have new case studies, we can introduce them and the model is automatically relearned, giving rise to a new model better adapted to the data available at that moment.

Algorithms of ML can perform different types of tasks: **Unsupervised machine learning**, **Reinforcement learning**, and **Supervised machine learning**.

Unsupervised methods are used to model the underlying structure -patterns, distribution- of data. They work with unlabelled data, which means that variables are not divided into inputs and outputs an, therefore none of the variables (output) are predicted by the model from the value of other variables (input), so there is no way to monitor the predictive behaviour of the model (hence 'unsupervised'). They are commonly used to perform exploratory and descriptive analyses on large datasets and to conduct three main tasks: *clustering*, *association*, and *dimensionality reduction*. *Clustering* is the process of grouping instances into similarity classes or clusters. The instances grouped in the same cluster are those that have similar values for the different features. *Association* analysis aims to find relationships between the variables in a dataset. *Dimensionality reduction* analysis is useful when the number of features (dimension) in a dataset is too high needs to be reducted. Some of the most commonly used unsupervised algorithms are Principal Component Analysis (PCA), and k-means Clustering.

The field of machine learning known as **Reinforcement learning** (RL) studies how intelligent agents should behave in a given environment in order to maximize the cumulative reward, and as unsupervised learning, does not require the presentation of labeled input/output pairings.

On the other hand, **Supervised methods** are used to solve problems when the available data consists of labeled instances, which means that each instance is a pair consisting of an input object, which is typically a vector, and an output object, which can be a single value or a vector. Based on samples of input-output pairs that form a training dataset, supervised learning methods aim to train an algorithm that accurately translates feature vectors (inputs) into output values (labels) for instances that are not yet visible to the model. This requires the learning algorithm to 'reasonably' generalize from the training data to real data. The so-called 'generalization error' is used to measure the statistical performance of an algorithm, and is estimated through a validation process that consists of using the model learned from the training dataset to predict the outputs corresponding to the instances of the validation (or test) dataset that acts as a set of new instances not seen by the model, for which we can compare the model predictions with the actually observed values. We speak of 'classification' when the outputs are finite categorical or discrete variables, and of 'regression' when they are continuous. Both tasks follow the same approach, building the predictive model ('classifier' or 'regression model', respectively) from the training database of instances, which are input-output pairs, so the resulting model learns to predict the value of the output variable(s) or label(s) for new instances for which their characteristics (input variables) are known (Bhavsar & Ganatra, 2012: 74). Supervised learning models look for the statistical association between variables, identify common properties shared in different case studies so that we can observe the same social action to acquire the ability to explain similar evidence as -probably- generated by the same cause. Since supervised methods work with labelled data, during the pre-processing phase it is required to ensure that the data is labelled, labelling it if necessary and, in some algorithms, discretising the continuous variables. Some of the most used supervised algorithms are random forest, neural networks, k-nearest neighbours, support vector machines and decision trees.

Generally, supervised methods are preferred over unsupervised for their predictive power, although they are not exclusive. In fact, some studies use unsupervised methods to explore the dataset before further analysis using supervised methods (e.g., Ahedo et al., 2021; Monna et al., 2020; Sharafi et al., 2016). Regarding the limitation of ML methods in archaeology, there are two main criticism that explain this fact. First, some researchers argue that these types of models are 'black-box' because the model design is not transparent. The modeller inputs the data and uses it to train the model and to predict the 'best' value (in some sense) for the output of a new instance. However, neither the training nor the prediction processes are observable and, therefore, it is difficult to assess the results. In this sense, SA can help to look inside the model and improve its explainability and interpretability because it explores the relationship among features and outcomes (Razavi et al., 2021). In its defense, it must be said that not all supervised ML methods are 'black-box'. Precisely, the one that we introduce in this work, the Bayesian Networks, are characterized by being 'white-box', as we will explain later.

Another disadvantage is the risk of 'losing the forest for the trees' if the dataset is too diversified and with few instances for every scenario. Ideally, all contexts should be equally well represented in the training dataset because otherwise one category would be prioritised, and reliable predictions would only be obtained for that category. This makes this method unsuitable for dealing with outliers (like most computational methods).

Of all the possible computational methos and machine learning algorithms, we have decided to focus this study on a supervised algorithm that is rarely used in archaeology but has great potential for dealing with archaeological data, **Bayesian networks** (BN). This methodology has gained importance in recent years in other fields such as healthcare or ecology. One of the most common uses of this method is to predict socio-ecological systems, such as the impact of human action to manage fires (e.g., Sevinc et al., 2020; Dlamini, 2011; Zwirglmaier et al., 2013), water resources (e.g., Phan et al., 2021; Castelletti & Soncini-Sessa, 2007), designing healthcare policies (Delgado et al., 2021; Spiegelhalter, 2004; Walsche & Burgman, 2010; Cruz-Ramírez et al., 2007), or risk management strategies (e.g., Pan et al., 2019; Sakar et al., 2021; Khan et al., 2018; Li et al., 2020). However, its application in archaeology is still rare. Whilst Bayesian statistics has gained popularity, especially for its application on radiocarbon dating (e.g., Otárola-Castillo et al., 2023; Crema, 2022; Pardo-Gordó et al., 2022) and some other fields (Otárola-Castillo et al., 2022; O'Shea, 2004; Hitchings, 2022; Krzyzanska et al., 2022), there are still very few applications of BN.

Bayesian networks (BN) are supervised ML models that are used for the classification task. More specifically, they are probabilistic algorithms, with a graphic component and some parameters that are conditioned probabilities, which encode the relationship of dependence between the variables associated with a random phenomenon of interest, which is the explored system. Like other statistical models, BN can be used to address questions about the nature of the data that go beyond the mere description of the observed sample (Nagarajan et al., 2013). The techniques used to derive these answers from new evidence are generally known as ‘inference’, although in the particular case of BN, the process of answering these questions is also known as ‘probabilistic reasoning’ or ‘belief updating’, while the questions themselves are called ‘queries’ (Pearl, 1988; Koller & Friedman, 2009).

One of the most interesting aspects of the BN is that they are ‘white-box’ models, and that means that they are transparent models that serve to understand and explore how the predictions are obtained (Naïm et al., 2011; Pearl, 1988; Wellman, 1990). Furthermore, it is not only used for prediction purposes, but explanatory knowledge can be gained from the graphic part of the model. These characteristics make BN a versatile probabilistic model in the current landscape of computational models, BN’s ability to integrate quantitative and qualitative data and account for uncertainty (e.g., Stritih et al., 2020; Marcot & Penman, 2019; Uusitalo, 2007; Afrin & Yodo, 2021).

As for the potential limitations of BN, they are similar to other supervised machine learning methods: they are restricted to labelled data, and on the other hand, they involve a trade off between ‘archaeological significance’ and ‘computational efficiency’. The latter is explained because the number of categories per variable must be limited with the aim of reducing the computational complexity, which necessarily leads to the simplification of the information available. All different values of the categories of the variables should ideally be distributed equally, but that is very difficult to achieve. The different values of the categories will be more or less represented in the dataset, and if there are few instances with a certain value, its prediction will be less accurate than other more represented values.

1.3. Bayesian Networks

1.3.1. Fundamentals

BN are based on the Bayes' theorem[1] (Franzese et al., 2012; Koller & Friedman, 2009; Moschovakis, 2001), that expresses the a posteriori probability of an event A based on an evidence B in terms of the a priori probability of the event A, and the likelihood of the evidence B, and can be expressed as follows **(1)**:

$$P(A \mid B) = \frac{P(A \bigcap B)}{P(B)} = \frac{P(A) \cdot P(B \mid A)}{P(B)} \quad \textbf{(1)}$$

Where in **(1)**, the following notations are used:

$P(A)$: the probability of A occurring (a prior probability of event A)

$P(B)$: the probability of B occurring (likelihood of the evidence B)

$P(A \mid B)$: the probability of A given B (a posterior probability of event A given the evidence B)

$P(B \mid A)$: the probability of B given A (likelihood of the evidence B under the assumption that A is true)

$P(A \bigcap B)$: the probability of both A and B occurring at the same time

To obtain these probabilities, BN employs probabilistic inference (Wheeler & Williamson, 2011; Hátek & Hartmann, 2010).

BN are probabilistic models to represent the relationship between a set of variables, those that affect a phenomenon subject to randomness that we are interested in studying. The model consists of a graphical part, which is a directed acyclic graph G, and a joint probability distribution P over the variables. The nodes of G represent the random variables whose directed edges correspond to the direct influence of one node on another (Koller & Friedman, 2009:51) with the restriction that cycles are not allowed, a 'cycle' being a closed path from a node to itself following in the direction of the edges and obtained by concatenation (hence 'acyclic'), and can be represented as follows **(2)**:

$$G = (V, E) \qquad \textbf{(2)}$$

[1] Sometime during the 1740s, the Reverend Thomas Bayes made the ingenious discovery that bears his name but then mysteriously abandoned it. Bayes never published his discovery, but his friend Richard Price found it among his notes after Bayes' death in 1761, re-edited it, and published it. Unfortunately, virtually no one seems to have read the paper, and Bayes' method lay cold until it was rediscovered independently by a different and far more renowned man, Pierre Simon Laplace, who gave it its modern mathematical form and scientific application — and then moved on to other methods.

G: Directed Acyclic Graph (DAG)
V: vertices (also called nodes), representing the variables
E: set of directed edges, formally expressed as a set of pairs of nodes indicating the departure and arrival nodes of each directed edge

For example, a node set V= {A, B, C, D} represent four variables, A, B, C, and D, and the set of directed arcs that relate them could be E= {(A, B), (B, C), (B, D), (C, D)}. Therefore, the corresponding DAG G= (V, E) is represented in **Figure 1**:

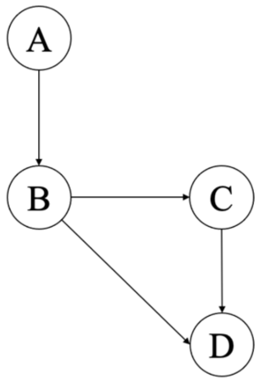

Figure 1. Directed graph of the example.

Figure 2 below shows some most common notations when working with DAGs: ancestor, parent, child, and descendant.

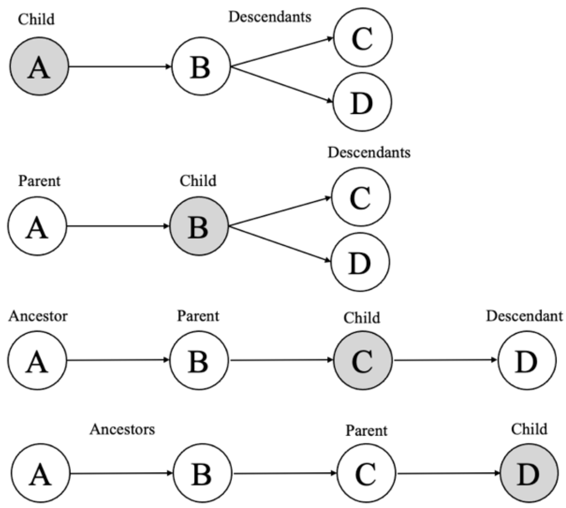

Figure 2. Example of directed graphs and the relationships encompassed between the nodes in the DAG. The colour grey defines the perspective in which relationships are defined.

As we have already anticipated, this structure is marked by *paths*, which are sequences of concatenated arcs or directed edges connecting two nodes, say A and B, the destination of one arc being the origin of the next in the sequence, with the first origin being A, and the last destiny being B. The structure is *acyclic* if it does not contain any cycle or loop.

What caracterises that pair (G, P), with G= (V, E) being a DAG, and P a joint probability distribution over variables in V, is a Bayesian network is that the directed arcs between nodes, E, represent conditional dependencies (not necessarily causal) that verify the **Markov condition** of P. The Markov condition states that each variable in V is independent on its non-descendants, conditioning to the state of all its parents in the DAG G (a variable can have more than one parent).

Following the example in **Figure 1**, the DAG represented there with a joint probability distribution P over V is a BN if they verify the Markov condition, which entails the following conditional relationship of independence between the variables in V (with respect to P):

- For node A: conditioning to its parents (none), A is independent of its non-descendants (none, since B, C and D are descendants of A).
- For node B: conditioning to its parent A, B is independent of its non-descendants (none, since C and D are descendants of B).
- For node C: conditioning to its parent B, C is independent of its non-descendant A.
- For node D: conditioning to its parents B and C, D is independent of its non-descendant A.

That is, Markov condition reduces to:

a) C is independent of A conditioning to B,
b) D is independent of A conditioning to B and C.

This means that say that the DAG in **Figure 1** jointly with a probability distribution P is a Bayesian network is equivalent to say that conditions a) and b) are both satisfied (with respect to P). Moreover, if it is the case, the joint probability distribution P can be expressed by the know as **Chain Rule** in the following way (as a product of probabilities conditioning any node to its parents, from the leaf nodes, which are the nodes without children, to the rood nodes, wich are those without parents) **(3)**:

$$P = (A = a, B = b, C = c, D = d) \; = \; P(D = d \;/\; B = b, C = c)P(C = c \;/\; B = b)P(B = b \;/\; A = a)P(A = a) \qquad (\mathbf{3})$$

The most common type of Bayesian networks are the ones known as 'static models', that is, those that represent a snapshot of the phenomenon under study, at a particular time, or that are invariant in time. By contrast, the Dynamic Bayesian networks are a specific type of models that incorporate temporal dynamics between the entities of interest (Murphy, 2002). In Dynamic Bayesian networks, each variable is represented by several nodes across time points, making them more complex and complicated. Dynamic BN are still very rarely applied and there is not any application in archaeology, for this reason, we have opted to focus on static BN which are the general type of traditional BN, although a possible line of future would focus precisely on the application of Dynamic BN to archaeological data.

In BN, the task of construction of the model from a database is known as *learning,* and it consists of two steps: *structure learning* and *parameter learning*. First, in *structure learning* the goal is to identify the graph structure, that is, the DAG G that best fits the data, according to certain criteria. Usually, there are three different approaches for achieving this, constraint-based, score-based, and hybrid learning (Nagarajan et al., 2013). In this work we follow the score-based structure learning, with the Bayesian Information Criterion (BIC) as score to try to maximise through an iterative heuristic search process based on the hill-climbing algorithm, implemented in the **hc** function of the R package **bnlearn** (Scutari & Denis, 2021).

Second, *parameters learning* is the process of implementing the estimation of the parameters of the distribution P of the Bayesian network (G,P) or, which is equivalent by the Chain Rule, the probabilities of each of the nodes conditioned to its parents in the DAG, which are, then, the 'parameters' of the model to estimate and can be represents in terms of **Conditional Probability Tables** (CPT). CPT list the probabilities of each node conditionining to all the possible combination of values of its parents. Parameters are estimated by the Maximum Likelihood Estimation (MLE), which is the most universally used model parameters estimation method in Statistics. The underlying idea is quite simple: if the likelihood of a model with respect to some data, which is the probability of observing with the model precisely those data that we have observed, is a measure of how well the model fits the data, we must choose the model parameters that maximise this measure of fit. As simple as brilliant, MLE was conceptualised by Sir Ronald Aylmer Fisher, and it is considered one of the most relevant contributions to Statistics of the 20th century.

Classical BN work with finite discrete or categorical variables and, if we have mixed data, that is, if some of the variables are continuous, it is necessary to discretize. There is always a trade-off between the accuracy of the discrete representation of the original data and the computational efficiency of the transformation because discretization always implies a loss of information while it simplifies. Nevertheless, thanks to this simplification it is possible to construct interpretable and simple models. There are different ways for defining the intervals in the discretization process of a continuous variables, such as using prior knowledge, heuristics (Venables & Ripley, 2002) or choosing the number of intervals and dividing equally among others

(Hartemink, 2001). Although it is possible to construct Gaussian BNs (if the predictor variables are all continuous) or hybrids (in the case of having mixed variables), in the research carried out in this thesis we have focused solely on classical BNs, leaving their application for research future.

It should be noted that BN provide statements of conditional independence but not of causality. They can be used to identify influence, but do not represent cause-and-effect relationships. As has been said, ‘correlation does not imply causation’ because there is no method of proving that cause-effect relationship between two variables actually occurs. Although it has been argued that ‘good’ Bayesian networks models represent the causal structure of the modelled system (Pearl, 2009), this is difficult to verify. In general, we are not able to identify a single ‘best’ causal network but rather a small set of likely causal networks that fit our knowledge of the data. BNs model the dependency relationship between variables but not allow establishing that these relationships are causal. Causality is not in the model but in our interpretation if we decide to make it.

1.3.2. Previous Applications of Bayesian Networks

BNs are used for data classification, that is, the output nodes can be configured to represent final classes, labels, types or concepts, and input nodes represent features, part-of relationships or any other aspect related to an explanation of the outputs. For instance, Barceló (1996) used a BN to solve the brittleness problem of pottery pots of archaeological classifications. As a result, the study provides different probabilities to different elements of the explanation. Another example is found in the study of Vuong et al. (2019) that uses BNs to classify ancient buildings, considering the inner modifications and cultural dynamic of the infrastructures. To address this issue, nodes record the presence/absence/relevance of different decorative and architectonic features (including Buddhism-inspired patterns/symbols, Taoism-inspired and Confucianism-inspired decorations). The data to construct the BN comes from interviews with users who gave their own beliefs and the traditional sentiments towards the buildings. Other examples of the application of BNs are the one developed by O’Shea (2004) to classify wreck sites, Osborn (2019) to classify bone assemblages according to their use in the past, or Barceló (2009) to infer social status in the past.

There are no BN models developed to specifically explore SES questions, but this method has gained some popularity in the field of ecology. There are some relevant applications in the agricultural domain such as the one developed by Cain (2001); a model framework designed to visualise the different processes encompassed in agricultural management practices. This application has been used primarily to incorporate ecological characteristics of agricultural land so that land managers can gain further understanding of land-use change (e.g., Dang et al., 2019; Kleeman et al., 2017; Andriyas & McKee, 2015; Aalders, 2008).

Similar to other modelling methods, BN can be combined with geospatial data, making it possible to visualise model results spatially (Aalders, 2008; Phan et al., 2016; Landuyt et al., 2013; Marcot & Penman, 2019). Many social factors typically have a spatial dimension of interest; therefore, it is often useful to manage social causal problems with an understanding of their spatial distribution and relationship (Chen & Pollino, 2012). By doing so, the probability outcomes of a Bayesian network model to assess local conditions can be used as input to GIS systems to create maps depicting how causal factors affect spatial variability in those estimations. In the same way, GIS tools can be employed to collect spatial input data that can be used to feed the network.

It should be noted that most archaeological studies using BN are built on the expert-based approach rather than be learned from data. They are built manually based on the prior knowledge, ideas, or assumptions of the researcher who designs it. These types of models are generally used as decision support systems thanks to the representation of an overview of all the parameters involved in the inspected system (Vos et al., 2021). Expert-based models tend to be used when little data is available, and the goal is to model the system for exploratory purposes such as what variables may be interesting to consider, for example. However, when we have enough data and the objective is not only to explain the model but also to predict the result of some situations, we use data-driven models. This kind of models are learned through machine learning techniques: the model is built from prior data and, following all the possible combinations of states of every node, the relationships among nodes are predicted.

To build BN models, different software is available: paid software such as NETICA (Norsys Software Corporation, 2007), Ergo (Norsys Software Corporation, 2007) or Hugin (Madsen et al., 2003) or open access such as R (R Core Team, 2022). For expert-based model building, the most common software is NETICA whereas for data-driven is R. The difference is the transparency of the model: in open-access software it is possible to examine every variable and link and, therefore, the resulting model is considered 'white-box' while paid software are 'black-box', which means that the building process is not visible or controllable by the user, reason why we have opted for the first alternative.

1.3.3. Comparison of Bayesian and Neural Networks

Neural networks are by far more common in archaeological studies, it has a longer trajectory than BN, the first studies applying this method date in the 90s (Barceló & Faura, 1997; Bell & Croson, 1998). For this reason, we decided to specify the differences between both metholodies.

Bayesian and Neural networks share some traits, as well as a part of their name, in that they are both supervised machine learning methodologies used for the classification task and are graphical models. But the similarities end there: the fact that they can be visually represented by some kind of 'network' does not imply that they are neither structurally nor functionally similar. In fact, they are clearly differentiated by their learning and prediction processes.

Bayesian Networks have already been introduced in detail in section 1.3.1. As for Neural Networks, they are inspired by information processing by biological brains. Their structure is determined by various successive 'layers' in which nodes represent interconnected 'neurons', whose connections represent synapses in the brain. The neurons receive inputs and give output values, and they can be essentially on or off, their activation being determined by a linear combination of the output values of the neurons of the previous 'layer' of the network. Inputs and outputs are linked through weights that must be learned from the training data. For this, we need a learning algorithm, and the most common one is the Backpropagation (Rummelhart et al., 1995; Wythoff, 1993; Hegazy et al., 1994; Kishore & Kaur, 2012) which transforms the numerical input into random weights between the input and the hidden layers, this information arrives to hidden artificial neurons, which carry out certain calculations and send a numeric output to the last layer. The output from hidden layers is also transformed by randomly initiated weights of links between the hidden and the output layers. This transformed signal arrives to the output layer and its artificial neurons are activated according to the intensity of the signal arrived and the particular activation function implemented. Obviously, because weights have been determined randomly during start-up, the final output is also the result of random decisions. The algorithm then compares what has been randomly calculated with the case studies from the database. If more cases are known, they are added to the dataset and the learning process begins again.

Unlike Bayesian Networks, which are explainable models ('white-box'), a Neural Network is a 'black-box' model that approaches the classification problem in a *connectionist paradigm*[2]. The popularity of Neural Networks (and 'deep learning', which refers to those Neural Network models that use multiple layers) in the last years has expanded the use of this approach, although the complexity of such networks has revealed their interpretability problems. Indeed, those models approach the problem of classification but do not explain how they carry it out. We can say that Neural Networks are now widely used due to their ability to produce fast results and to work with large databases, but this is only acceptable if the problem of model explainability is obviated. Otherwise, it is better to use explanatory predictive models, such as Bayesian Networks, and we have used in the research included in this thesis precisely for this reason.

In conclusion, althoughboth Bayesian and Neural networks can be used to model the relationships between inputs (evidence) and outputs (predicted labels) in a non-linear way and they are learned from a dataset and are used for classification. Neural networks have limitations compared to BNs: a Neural network is a 'black-box' algorithm, meaning that the learning process involving weights and neurons is not transparent nor explainable, so the user can only observe the dataset and the final outputs, but not the learning or the prediction processes. On the other hand, BNs are learned with a transparent procedure, the models are explaniables and their predictions are justificable: we can clearly communicate to researchers in any discipline what the model accomplishes, as well as the information it uses and the evidence or knowledge that underlies each part of the model. Conversely, Neural network models cannot accomplish this.

A perhaps less obvious reason in favour of Bayesian networks is their flexibility and modularity. With a Bayesian network, we can train some parts of the model from data, but others can be built from expert knowledge, and this cannot be replaced by a Neural network. In an applied setting, such as archaeology, we need not only models that are accurate in their predictions (functional requirement), but also justifiable to experts and easy to update in a rapidly changing world (non-functional requirements). We cannot discount the importance of non-functional requirements, and it is crucial to keep in mind that while Neural networks, by their own construction, fulfill functional but not non-functional requirements, Bayesian networks meet both.

[2] Neural Networks are algorithms used in the field of Artificial Intelligence to create more intelligent machines. The term 'connectionism' refers to an approach in cognitive science that aims to use Neural Networks to explain and reproduce mental procedures. According to connectionism, learning is a congnitive procedure accomplished by adjusting connection strengths between neurons in response to experience (Smolensky, 1999).

1.4. Research Paper

1.4.1. **Palacios, O.** (2023). Aplicación del aprendizaje automático en Arqueología: ¿Un cambio de paradigma?. *Vegueta. Anuario de la Facultad de Geografía e Historia, 23*(1), 147-186. https://doi.org/10.51349/veg.2023.1.06

Aplicación del Aprendizaje Automático en Arqueología: ¿Un Cambio de Paradigma?

Application of Machine Learning in Archaeology: a paradigm shift?

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Resumen

Aunque las primeras aplicaciones de aprendizaje automático en arqueología datan de finales de los años 90, no ha sido hasta el año 2019 cuando su uso se ha empezado a extender. ¿Qué ventajas tiene esta metodología respecto a otros métodos con una trayectoria más larga en arqueología? ¿Se puede aplicar en todos los ámbitos de estudio? La presente contribución tiene el objetivo de dar respuesta a estas cuestiones a través de una exhaustiva revisión de los estudios arqueológicos realizados con esta metodología y desarrollando un modelo con un algoritmo concreto, las redes bayesianas, para explorar sus beneficios y limitaciones.
Palabras clave: aprendizaje automático, arqueología, metodología, redes bayesianas, beneficios y limitaciones

Abstract

Despite first applications of machine learning in archaeology date back to the late 90s, it was not until 2019 that its use began to spread. What advantages does this methodology have that the previous methods do not have? Can it be applied in all fields of study? This contribution aims to answer these questions through an exhaustive review of the archaeological studies carried out with this methodology and by developing a model with a specific algorithm, Bayesian networks, to explore its benefits and limitations.
Keywords*:* machine learning, archaeology, methodology, Bayesian networks, benefits and limitations.

1. INTRODUCCIÓN

Entender el pasado es el objetivo de la ciencia arqueológica. ¿Por qué una sociedad vivió en un sitio y no en otro? ¿Qué comía y por qué prefería unos recursos a otros? ¿Cuánta gente vivía en un poblado y cómo se organizaban? Estas cuestiones son tan solo algunas de las múltiples preguntas a las que se intenta dar respuesta a partir del registro arqueológico. Partiendo de la premisa que para comprender un sistema social es necesario considerar sus dinámicas socioeconómicas y su entorno ecológico, en los años 50 se desarrolló la Teoría de los Sistemas Complejos (TSC) (von Bertalanffy, 1950) que proponía investigar a las sociedades como sistemas complejos con diferentes variables y relaciones no lineales. Esta innovación representó un cambio radical en la investigación arqueológica, puesto que TSC aportó una nueva manera de entender el dinamismo en el pasado a partir del concepto de sistemas socioecológicos.

La estructura de un sistema socioecológico está definida por la interacción entre comportamientos sociales (ej., tipo de dieta, organización doméstica y del trabajo) con aspectos ecológicos definidos por la localización dónde se llevó a cabo la acción social (ej., productividad del suelo, temperatura media). Esta nueva conceptualización representó un progreso en la modelización del comportamiento social como un sistema influenciado por muchas variables diferentes y con distinta intensidad (ej., Neto *et al*., 2018; Zeder, 2017; Smith, 2015). Para modelar esta estructura, podemos dividir el sistema en tres elementos distintos: los *inputs* (los datos conocidos), los *outputs* (lo que queremos descubrir, la cuestión investigada) y el/los *mecanismo/s* (los procesos y estructura de relaciones a través de los cuales interactúan los inputs y los outputs). Pongamos el caso que queremos comprender por qué las sociedades neolíticas practicaban la agricultura y la ganadería en lugar de la caza, la recolección o la pesca (*output*). Una manera de explorar esta cuestión sería a partir de los datos de las variables climáticas o topográficas (*inputs*). Esta aproximación se basa en la idea de que los diferentes elementos están relacionados entre sí y, por tanto, estudiando la fuerza de estas relaciones y su organización (*mecanismo*), podremos comprender cómo funcionaron en el pasado.

Tomando en cuenta esta aproximación teórica, los métodos cuantitativos y computacionales permiten explorar estas relaciones entre elementos y predecir información desconocida o no observada de los sistemas a partir de la que sí que tenemos registrada (Tewari *et al*., 2020).

Con este objetivo, en arqueología hay principalmente dos líneas de estudio: los métodos matemáticos tradicionales (tienen mayormente una función descriptiva) y, los computacionales, (con mayor capacidad interpretativa y exploratorio) (Barceló, 2008). Concretamente, dentro de los métodos computacionales se encuentra la simulación, que permite experimentar con diferentes escenarios *in silico* (desarrollados vía simulación computacional) y evaluar sus resultados para compararlos, finalmente, con el registro arqueológico. Esta clase de modelos se pueden clasificar en dos categorías: los modelos basados en agentes (*agent-based modelling*) y los modelos dinámicos (*dynamic modelling*). Se diferencian por la metodología que utilizan, ya que los modelos basados en agentes se construyen a través de un software específico como NetLogo (Wilensky, 1999), mientras que en los modelos dinámicos se utilizan ecuaciones diferenciales. Algunos ejemplos paradigmáticos de modelos basados en agentes centrados en la investigación de sistemas socioecológicos del pasado son 'The Village Ecodynamics' (Kohler y Varien, 2012), 'WELASSIMO' (Baum *et al*., 2016; Baum, 2016), 'The Mediterranean Landscape Project' (Barton *et al.,* 2012; Barton *et al*., 2010; Ullah, 2011; Ullah y Bergin, 2012). Asimismo, los modelos dinámicos más representativos de dinámicas sociales son el modelo 'Prey-Predator' (Lotka, 1920; Volterra, 1926), 'Wave of advance' (Ammerman y Cavalli-Sforza, 1979, 2014), a partir de los cuales se han planteado otras propuestas modelando la expansión neolítica (Isern *et al*., 2017; Fort, 2022).

Por otro lado, los métodos computacionales también incluyen la metodología del aprendizaje automático (*machine learning*), AA, es una rama de la Inteligencia artificial basada en la utilización de una 'máquina' (ordenador) para aprender automáticamente nueva información a partir de escenarios anteriores ya conocidos. Emplea el mismo razonamiento que el método inductivo tradicional, por ejemplo, para interpretar un yacimiento: el arqueólogo lo compara con otros yacimientos del mismo contexto con características similares y, basándose en su propio criterio (el cual está modelado por su educación, experiencia o convicciones), propone la interpretación más probable. Estos métodos computacionales pueden generar modelos predictivos, es decir, que sus resultados se pueden utilizar para predecir eventos desconocidos o no observados (Tewari *et al.,* 2020), pero la diferencia es que en el aprendizaje automático, este proceso de aprendizaje es realizado por el ordenador a través de un algoritmo que explora la base de datos, identifica las tendencias y, basándose en estas, predice los casos futuros (o los pasados, como en arqueología). Por lo tanto, en AA no se necesitan hipótesis previas sobre las relaciones entre las variables porque el modelo se aprende a partir de los datos conocidos. Por contra, en los modelos estadísticos y de simulación, las relaciones entre las variables se tienen que conocer de antemano para definir su estructura.

Pese a los múltiples beneficios de la metodología de AA, su aplicación en arqueología todavía es reducida dado que hay pocos estudios realizados que hagan una recopilación de los campos de análisis dónde se ha aplicado, el tipo de algoritmos utilizados o desarrollen un análisis crítico sobre sus puntos fuertes y debilidades. En este sentido, contrasta con otras áreas de investigación dónde sí que ha habido esfuerzos para sistematizar su aplicación y definir su aplicabilidad (ej., Edeh *et al*., 2021). Concretamente, desde otras ciencias sociales se han llevado a cabo diversos estudios identificando las limitaciones del método y se han definido propuestas para superarlas (ej., Radford y Joseph, 2020; Crowford *et al*., 2019; Jacobs y Wallach, 2019; Lazer y Radford, 2017).

Para la modelización de sistemas socioecológicos en arqueología, es más común emplear las simulaciones basadas en agentes, dónde se han implementado numerosos estudios explorando su capacidad de adecuación para aplicarlo en arqueología y se han desarrollado pautas de buenas prácticas (por ejemplo, Grimm y Railsback, 2012; Müller *et al*., 2014). A nivel de AA en arqueología, hay sobre todo estudios de introducción del método (por ejemplo, Bickler, 2021; Davis, 2020a, 2020b; Ramazzoti, 2020; Mackenzie, 2017) pero no hay ninguna publicación que resuma los algoritmos disponibles, para qué sirven, cómo han sido aplicados en arqueología (o no) y evalúe su idoneidad para investigar sistemas socioecológicos. En consecuencia, la presente contribución tiene los objetivos siguientes:

- Caracterizar la aplicación de la metodología del aprendizaje automático en arqueología y, más específicamente, en el ámbito de estudio de sistemas socioecológicos.
- Definir los beneficios y limitaciones del método en este ámbito de investigación**.**

Para abordar estos objetivos, se ha empleado una doble metodología combinando una detallada revisión bibliográfica de los trabajos desarrollados en el ámbito arqueológico empleando AA, especialmente centrado en su aplicación para explorar sistemas socioecológicos. Adicionalmente, se ha realizado una aplicación práctica con un método de AA, las redes Bayesianas, para evaluar la idoneidad de aplicación de este método en este ámbito de estudio.

2. METODOLOGÍA

2.1. Principios del aprendizaje automático

Para la construcción de un modelo de aprendizaje automático es muy importante tener disponible una base de datos con un gran número de casos para poder clasificar y predecir los casos desconocidos. En función del tipo de datos y la cuestión planteada, un algoritmo puede que funcione mejor que otros. Hay diversos tipos de algoritmos en AA que sirven para distintas finalidades y se agrupan en dos clases principales: métodos *no supervisados* y *supervisados* (Alloghani *et al.*, 2020) (**Tabla 1**). Los métodos *no supervisados* se emplean para identificar patrones, estructuras y distribuciones con datos sin etiquetar (es decir, no diferenciados); se utilizan para descubrir patrones en los datos sin que el/la investigador/a intervenga, por este motivo se llaman ‘no supervisados’ (Dhall *et al*., 2020). El objetivo es desarrollar un modelo para identificar la estructura subyacente o distribución de los datos para aprender nuevos casos o escenarios. Es un método especialmente adecuado para desarrollar análisis exploratorios y descriptivos de grandes bases de datos. Esta aproximación permite agrupar objetos ‘parecidos’ pero sin seguir unas normas (ver Kohonen, 2001; Engel y van der Broeck, 2001 para una descripción de los mecanismos de agrupación), a diferencia de la clasificación que sigue una normal prestablecida y permite diferenciar los objetos en clases.

	MÉTODOS NO SUPERVISADOS	MÉTODOS SEMI-SUPERVISADOS	MÉTODOS SUPERVISADOS
Tipo de datos	No etiquetados	No etiquetados	Etiquetados
Función	**(a)** Reducir la dimensionalidad de los datos	Construir etiquetas a partir de los casos anteriores	Clasificación de nuevos casos a partir de una norma general
	(b) Detección de outliers	Para realizar funciones supervisadas, pero con datos no supervisados	Regresión para predecir nuevos casos a partir de los conocidos
	(c) Agrupación de casos		
Algoritmos principales	**(a)** Principal component analysis, Independent component analysis, Manifold learning, Autoencoders **(b)** Isolation forest, Local outlier factor, Minimum covariance determinant **(c)** K-means, Hierarchical and Spectral clustering, DBSCAN y OPTICS, Affinity propagation, Mean shift y BIRCH, Gaussian mixture models, Self-organising map, Discriminant Analysis	Active learning	Support vector machine K-nearest neighbour Deep learning (Neural networks, Convolutional neural networks, Deep belief networks, Deep reinforcement learning) Decision trees Regression trees Classification and regression trees (CART) Logistic regression Random forest Bayesian networks

Tabla 1. Clasificación de los principales algoritmos de aprendizaje automático. Fuente: Elaboración propia.

Sin embargo, los métodos no supervisados no pueden realizar funciones de clasificación dado que se necesitan datos etiquetados y con sus valores agrupados en clases (requisito que marca la distinción entre ambos métodos). Es así como esta función se realiza con *métodos supervisados*, los cuales tienen el objetivo de identificar la interpretación más probable considerando todas las posibles explicaciones conocidas. Si bien los métodos no supervisados están limitados a analizar y agrupar datos sin etiquetar, los métodos supervisados se aplican a datos etiquetados y usan algoritmos específicos para predecir modelos a partir de los datos (esto también se emplea para validar los modelos) y hacer nuevas predicciones. Los métodos supervisados no solamente permiten clasificar y organizar los datos en categorías, sino que permiten aprender nuevos datos a partir de los ya conocidos para, finalmente, desarrollar interpretaciones más robustas (Bickler, 2021). Algunos autores proponen también los métodos semi-supervisados (Klassen *et al*., 2018), empleados cuando los datos no están etiquetados, pero se quieren realizar funciones supervisadas.

Independientemente del método, la metodología de AA se caracteriza por necesitar un gran volumen de casos para poder computar el modelo, puesto que el modelo se aprende a partir de los casos anteriores. Este aspecto puede representar una desventaja en arqueología porque los datos obtenidos son a veces difíciles de cuantificar y no se suelen tener muchos casos con las mismas características, calculados de la misma manera, bien documentados, para crear modelos. Por otra parte, en la última década se ha extendido la práctica de publicar las bases de datos en abierto y, así, datos que en sí son lentos de generar e interpretar, se han democratizado, proporcionando la oportunidad de ampliar los estudios a través de la reutilización de estos datos (Faniel *et al.,* 2013). La principal crítica del AA es que genera modelos difíciles de interpretar (ej., Radford y Joseph, 2020; Jacobs y Wallach, 2019) porque suelen ser cajas negras (*black boxes*), lo que significa que desconocemos los mecanismos internos o procesos a través de los cuales se diseña el modelo. En algunos casos, puede que para el/la investigador/a no sea relevante conocer cómo se ha diseñado el modelo, pero en otros, a lo mejor tener un control total del desarrollo del modelo sea crucial para interpretar cómo se han obtenido los resultados de los outputs.

2.2. Aplicación del aprendizaje automático en arqueología

Con el fin cuantificar la aplicación de esta metodología en el campo arqueológico, se ha realizado una búsqueda de artículos en dos bases de datos bibliográficos, Scopus (Elsevier, 2004) y Web of Science (Clarivate Analytics, 2022), de trabajos que tratan de "machine learning" (campo 'all fields') y "archaeology" (campo "article title, abstract, keywords") en "English/ Spanish/ French". Dado que es un método bastante reciente, la búsqueda no se restringió por año de publicación. En Scopus se obtuvieron 808 resultados y en Web of Science 87. A continuación, se analizó exhaustivamente cada artículo y las referencias a otros casos de estudios en la bibliografía con la finalidad de obtener un registro más completo. Los criterios de selección de los artículos han sido los siguientes:

- Utilizan un algoritmo de AA (individualmente o en conjunción con otros algoritmos o métodos fuera de AA) para investigar una cuestión arqueológica
- Se han excluido los artículos de análisis metodológico o teórico
- Se han excluido los artículos que mencionaban AA, pero utilizaban otro método para desarrollar la investigación
- Se han excluido los artículos que mencionaba la arqueología como una posible aplicación de AA, pero el caso de estudio era de otro tema no relacionado

Seguidamente, se construyó la base de datos con los artículos seleccionados y se agruparon según (i) la cuestión arqueológica que exploraba (por ejemplo, si tratan sobre la gestión socioeconómica del pasado o sobre el reconocimiento de patrones de materiales arqueológicos) y (ii) el algoritmo o algoritmos de AA que utilizan. En total, se han seleccionado 91 artículos (**Apéndice Tabla 1**). La razón de este bajo índice es debido a que las grandes bases de datos bibliográficos también habían considerado los artículos que mencionaban la arqueología como una aplicación más en AA, pero el estudio trataba sobre otro tema, o artículos arqueológicos que mencionaban la posibilidad de llevar a cabo el análisis con AA, pero finalmente empleaban otro método cuantitativo o computacional. Adicionalmente, cabe mencionar que, en diversos casos, los modelos se construyen principalmente para probar el método más que para explorar preguntas arqueológicas. Así mismo, hay algunos estudios que no son replicables porque el algoritmo no se especifica, solo se dice que utilizan 'un algoritmo de aprendizaje automático'. En este caso, no se han considerado en la base de datos. También hay muchos modelos que están construidos desde el 'conocimiento experto' y, por lo tanto, no son modelos de AA.

A partir de la recopilación bibliográfica, se han diferenciado cuatro temáticas principales dentro de arqueología que emplean AA. Cada grupo engloba aplicaciones con objetivos diferentes, pero que tratan del mismo tema o trabajan con el mismo tipo de material. En primer lugar, los análisis de **materiales y estructuras** incluyen el procesamiento de imágenes (ej. Colmenero-Fernández y Feito, 2021), afiliación cultural (ej. Grove y Blinckhorn, 2020), estructuras (ej. Monna *et al.*, 2020), arte (Tsigkas *et al.*, 2020), cerámica (Gualandi *et al.*, 2021) o marcas de procesamiento (ej. Cifuentes-Alcoberas y Domínguez-Rodrigo, 2019; Courtney *et al.*, 2019). En segundo lugar, las aplicaciones para los análisis **espaciales** se centran en predecir la ubicación de asentamientos desconocidos (ej. Bonhage *et al.*, 2021; Reich *et al.*, 2021) y la posible localización de estructuras específicas como, por ejemplo, de enterramiento (ej. Berganzo-Besga *et al.*, 2021; Chen *et al.*, 2021; Caspari y Crespo, 2019). También se emplea en estudios espaciales con el objetivo de diseñar estrategias para la prevención, protección y gestión del patrimonio arqueológico (ej., Friggens *et al.*, 2021; Davis *et al.*, 2021; Xu *et al.*, 2019; Castiello y Tonini, 2019). En tercer lugar, los estudios de **sistemas socioecológicos** utilizan AA para explorar diversas temáticas como los movimientos migratorios (Vahdati *et al.*, 2019), la gestión de los recursos sociales y económicos (ej. Davis y Douglas, 2021; Ahedo *et al.*, 2021, 2019; Burry *et al.*, 2018; Barceló *et al.*, 2015; Alberti, 2014) y las dinámicas culturales (Hyafil y Baumard, 2022). Finalmente, también se emplea para analizar **documentación escrita**, concretamente para clasificar caracteres y palabras (ej. Haliassos *et al.*, 2020; Ramya *et al.*, 2019; Brandsen *et al.*, 2020), traducir textos (Sanders, 2018) y para crear aplicaciones patrimoniales para difundir la documentación escrita (Fabricius, 2022).

Las primeras aplicaciones de AA en arqueología datan de inicios del 2000 con su aplicación para clasificar materiales arqueológicos, principalmente cerámica, y para identificar la ubicación de asentamientos (**Gráfico 1**). En 2014 se publicaron los primeros estudios abordando el análisis de dinámicas socioecológicas, pero de forma muy minoritaria, tendencia que se conserva actualmente. Los estudios con AA para analizar documentación escrita siguen una dinámica parecida, debido a que sus primeras aplicaciones datan en 2018, pero actualmente su aplicación es todavía limitada. Por otro lado, el número de estudios de análisis de materiales y estructuras y estudios espaciales augmentaron considerablemente en 2019 y esta dinámica se ha mantenido hasta la fecha. A nivel de importancia relativa, el mayor número de estudios publicados utilizando AA son los estudios de materiales y estructuras (49,45%), seguidos por los estudios espaciales (29,67%), de sistemas socioecológicos (14,29%) y de documentación escrita (6,59%).

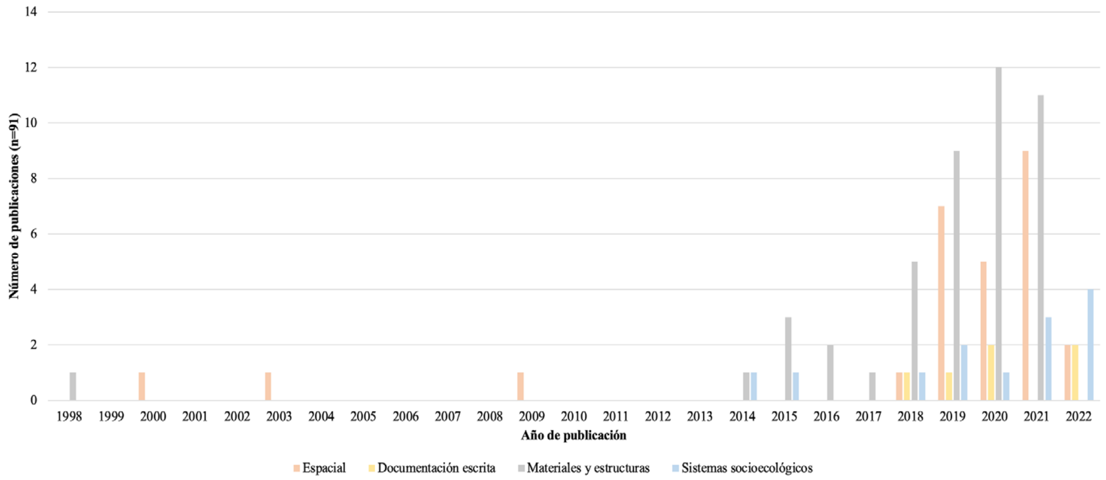

Gráfico 1. Cuantificación de los estudios realizados en arqueología, empleando aprendizaje automático, divididos por año y por campo de estudio.

Respecto a qué métodos de AA son las más comunes en arqueología, el 90% de los estudios analizados utilizan métodos supervisados, siendo los algoritmos más utilizados el *deep learning* (incluye *neural networks*, *convolutional neural networks*, *deep belief networks* y *deep reinforcement learning*) y el *random forest* (**Gráfico 2**). Los métodos no supervisados y semi-supervisados exclusivamente se emplean para analizar materiales y estudiar sistemas socioecológicos. Normalmente, se emplean este tipo de algoritmos en combinación con un algoritmo supervisado. En algunos casos, como por ejemplo Monna *et al.*, 2020 y Courtney *et al.*, 2019, se exploran diferentes algoritmos con el objetivo de evaluar cuál es el que produce mejores resultados.

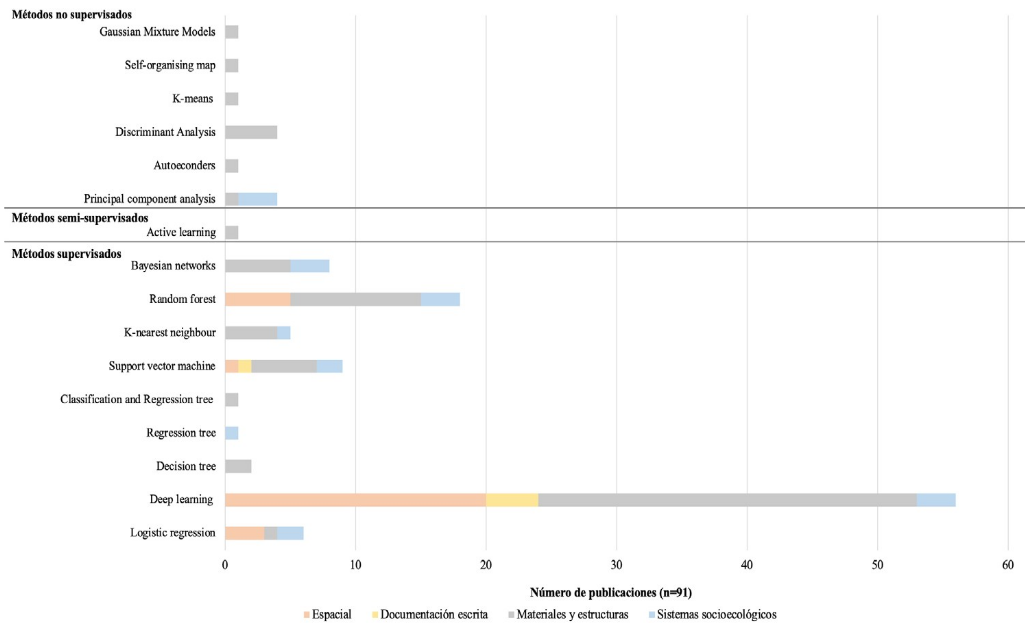

Gráfico 2. Algoritmos supervisados, no supervisados y semi-supervisados divididos por cada ámbito de investigación. Fuente: Elaboración propia.

En el caso de los modelos socioecológicos, observamos que su uso es muy minoritario y emplea diversos algoritmos supervisados (*logistic regression*, *deep learning*, *regression tree*, *support vector machine*, *bayesian networks*, *random forest* y *k-nearest neighbour*) y no supervisados (solamente el algoritmo de *principal component analysis*). Para poder interpretar esta diversidad en los algoritmos empleados para explorar este ámbito de la investigación, sería necesario identificar y calcular qué métodos son los más comunes para abordar estas cuestiones e identificar posibles diferencias. En vista de que sería muy costoso aplicar todos los algoritmos de AA para compararlos, en el presente estudio se ha optado por aplicar las redes bayesianas (Koller y Friedman, 2009; Neapolitan, 2004), un algoritmo probabilístico de AA supervisado que se caracteriza por ser un modelo de *caja blanca (White box)*. Aparte de producir modelos predictivos (como todos los algoritmos supervisados), también son explicativos, dado que a través de su representación se obtiene información sobre cómo las variables se relacionan; y estas relaciones indican correlaciones. Por otro lado, las redes bayesianas se representan en forma de *modelo directo acíclico* que permiten obtener la distribución de probabilidad de las variables del modelo y, por tanto, obtener la probabilidad a partir de las probabilidades condicionales de los nodos con los que está relacionado (**Figura 1**).

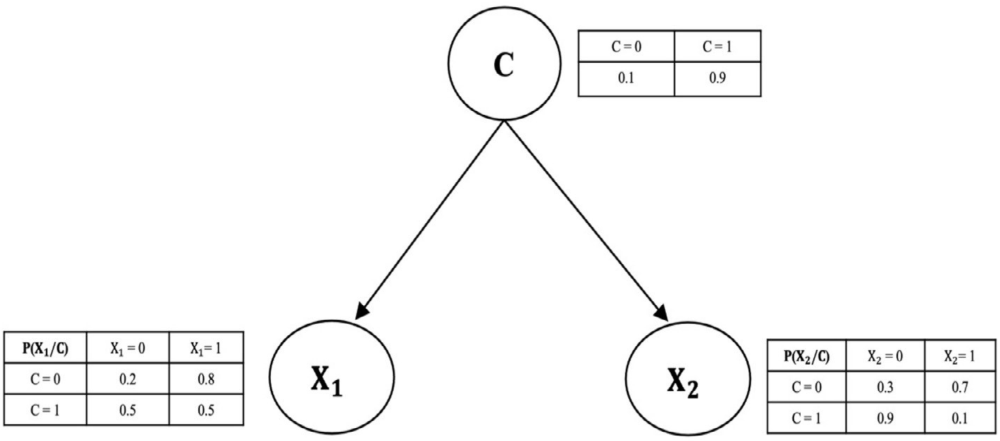

Figura 1. Ejemplo de una red bayesiana simple. C es el padre de X_1 y X_2, las cualescomputan las probabilidades teniendo en cuenta C. Fuente: Elaboración propia.

2.3. Construcción de un modelo socioecológico con redes bayesianas

El objetivo del modelo construido para explorar la aplicación de AA y, concretamente, el algoritmo de redes bayesianas es definir **si el tipo de subsistencia de las comunidades agroganaderas de pequeña escala están influenciadas por las condiciones ecológicas de su entorno**. El modelo se ha construido en cinco fases: (i) Creación de la base de datos; (ii) Preprocesamiento de los datos; (iii) Construcción del modelo; (iv) Validación del modelo; (v) Aplicación del modelo y obtención de los resultados (**Figura 2**).

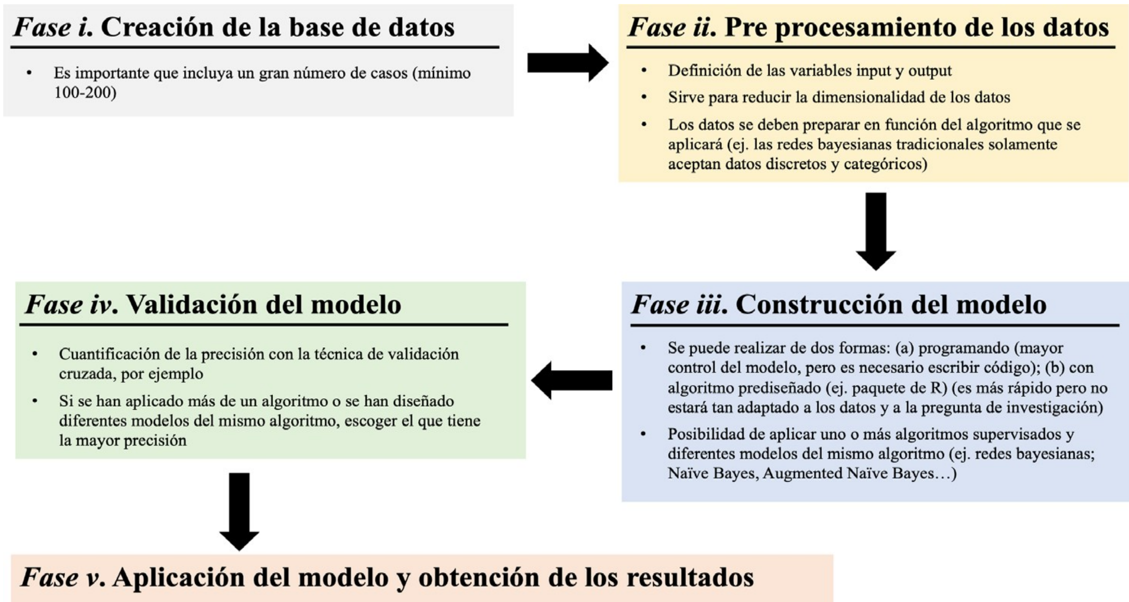

Figura 2. Esquema de proceso de modelización. Fuente: Elaboración propia.

***Fase i.* Creación de la base de datos:** para estudiar esta cuestión, se ha seguido la línea de investigación de estudios interdisciplinares que emplean los datos históricos y etnográficos para comprender las dinámicas socioeconómicas del pasado (ej., Peregrine, 1996; Gantley *et al.*, 2018; Ferraro *et al.*, 2019; Desmond, 2014; Watts *et al.,* 2022; Atkinson y Whitehouse, 2011). No se implica que a partir de la etnografía podamos inferir procesos de las comunidades del pasado, pero sí se utiliza esta disciplina para sugerir y cuantificar la viabilidad de algunas prácticas que no son observables en el registro arqueológico porque no son materiales (ej. preferencias, decisiones, prácticas sociales, etc.). En total, se recopilaron 265 sociedades etnográficas de pequeña escala (menos de 1000 habitantes) y agroganaderas (al menos el 50% de su subsistencia debe estar basada en recursos agrícolas y/o ganaderos) de la base de datos D-PLACE (Kirby *et al*., 2016) (**Apéndice Tabla 2**).

***Fase ii.* Preprocesamiento de los datos:** todo el procesamiento, creación del modelo, validación y obtención de los resultados se ha desarrollado con R (R Core Team, 2022) y el script está disponible en **Apéndice Script 1**. Una vez los datos de las sociedades estaban recopilados, se procedió a su procesamiento. Las redes bayesianas estándares no procesan los datos continuos, de manera que se han discretizado todas las variables con la función **discretize** del *paquete arules*, estableciendo las categorías a partir de su distribución ideal en dos, tres o cuatro clases (**Tabla 2**). En el proceso de discretización se ha tenido en cuenta agrupar los valores de cada variable en número reducido de clases porque las redes calculan la probabilidad de cada valor condicionada a las probabilidades de los valores de las otras variables y, consecuentemente, el modelo aumenta su complejidad computacional a medida que aumentamos las clases. También es necesario tener en cuenta que, si las clases están igualmente representadas, es decir, que tienen el mismo número de casos en cada una, el modelo tendrá la misma capacidad de predicción para todos los valores y evitar que priorice los valores más representados. En consecuencia, variables de caza, recolección o pesca, por ejemplo, tienen agrupados todos los casos de intensidades entre el 15 – 100 % en una única categoría que se llama '>150', mientras que agricultura, que tiene muchos más casos de intensidades superiores al 15%. tiene más categorías para representar este intervalo.

Variables	Categorías		
Distancia a la costa	<140	140-600	>=600
Elevación	<300	300-800	>=800
Pendiente	<0,75	0,75-2,5	>=2,5
Temperatura media anual	<5	5-20	>=20
Variación de la temperatura media	<1,3	1,3-20	>=20
Constancia de la temperatura	<0,5	0,5-0,7	>=0,7
Contingencia de la temperatura	<0,12	0,12-0,2	>=0,2
Precipitación media mensual	<1,06e+05	1,06e+05-1,67e+05	>=1,67e+05
Variación de la precipitación media	<7,86e+09	7,86e+09-1,49e+10	>=1,49e+10
Constancia de la precipitación	<0,4	0,4-0,5	>=0,5
Contingencia de la precipitación	<0,2	0,2-0,3	>=0,3
Producción primaria neta media mensual	<1	1-3	>=3
Constancia de la producción primaria neta	<0,2	0,2-0,3	>=0,3
Contingencia de la producción primaria neta	<0,2	0,2-0,3	>=0,3
Agricultura	<45	45-75	>=75
Ganadería	<15	15-45	>=45
Caza	<15	>=15	
Recolección	<15	>=15	
Pesca	<15	>=15	

Tabla 2. Variables de la base de datos con sus categorías discretizadas. Fuente: Elaboración propia.

Fase iii. **Construcción de los modelos:** los estudios anteriores de redes bayesianas para modelar sistemas socioecológicos empleaban la estructura de Naïve Bayes (NB), que es un algoritmo que tiene una estructura predeterminada en la cual únicamente hay un output y todos los inputs están relacionados con este. Es así como NB se asume que los inputs no están relacionados entre ellos (por ejemplo, que las variables ecológicas como la temperatura y la precipitación no están relacionadas) y que todos los inputs están relacionados con el output (por ejemplo, que la elevación está igual de relacionada que la temperatura con la agricultura). Dado que Teoría de los Sistemas Complejos argumenta que las variables de un sistema están interrelacionadas de manera compleja y no linear, en este estudio, se ha optado por modelar el mismo sistema con otras estructuras más complejas como el Augmented Naïve Bayes (ANB) (permite las interrelaciones entre inputs) y sin restricciones (permite más de un output y también incluye las interrelaciones entre outputs) para establecer comparaciones con el modelo NB (en la **Tabla 3** están más detalladas las diferencias entre los tres modelos).

Características	Modelo Naïve Bayes	Modelo Augmented Naïve Bayes	Modelo sin restricciones
Algoritmo de aprendizaje de la estructura	Estructura fija con relación de un output a los inputs (caja negra)	Hill-climbing con el criterio AIC o BIC. Relaciones de un output a inputs, las relaciones entre inputs están permitidas (caja blanca)	Hill-climbing con el criterio AIC o BIC. Relaciones entre outputs a inputs a la vez, interrelaciones entre outputs e interrelaciones entre inputs están permitidas (caja blanca)
Objetivo	Predicción	Predicción y explicativa (relaciones entre inputs)	Predicción y explicativa (relaciones output - input, entre inputs y entre outputs)
Beneficios	Simple y buen equilibrio entre capacidad predictiva y simplicidad Relaciones binarias (un input y un output)	Permite relaciones entre los inputs, pero sólo un output a la vez Relaciones binarias	Representa las relaciones entre todos los outputs y todos los inputs a la vez
Limitaciones	Ignora las relaciones entre inputs y entre outputs	Ignora las relaciones entre inputs y entre outputs	Más complejo que los otros modelos y, por lo tanto, es necesaria más potencia computacional

Tabla 3. Principales características de los tres modelos de las redes bayesianas. Fuente: Elaboración propia.

Los modelos se han aprendido con el *paquete bnlearn* (Scutari y Denis, 2021) que implementa la estructura y el aprendizaje paramétrico. Esta estructura ha sido definida siguiendo los criterios y parámetros más comunes en la implementación de redes bayesianas en los diferentes ámbitos de investigación (ej., Atienza *et al*., 2022; Palacios *et al.,* 2022; Fan *et al.,* 2022; Chobtham y Constantinou, 2020). Se ha utilizado el algoritmo hill-climbing del *paquete gRain* (Højsgaard, 2012) para aprender la estructura de búsqueda y puntuación de la representación ya que lo hace a partir de la combinación que maximiza la función de puntuación. Se tienen en cuenta dos funciones de puntuación, el Bayesian Information Criterion (BIC) y el Akaike Information Criterion (AIC). Ambos criterios son logaritmos de probabilidad, pero AIC penaliza menos y, por lo tanto, crea grafos con más conexiones. Los parámetros se han establecido siguiendo el criterio de máxima verosimilitud, que representa el procedimiento más común.

Fase iv. **Validación de los modelos:** para calcular la precisión del modelo se utilizó la técnica de validación cruzada donde k=5, es decir, se emplearon cuatro casos para predecir el quinto y, comparando la predicción con el resultado original, se obtiene el valor de precisión. Este proceso se lleva a cabo cinco veces para cada modelo. Se ha seleccionado k=5 porque estudios recientes indican que este número es suficiente para validar la robustez del modelo y, además, tiene la ventaja de ahorrar tiempo y capacidad computacional (Marcot y Hanea, 2020).

A continuación, para seleccionar el modelo que produjera resultados con mayor precisión, se empleó la prueba t-test para comparar primero el modelo NB con el modelo ANB y, el que tenía el valor más alto, se contrastó con el modelo sin restricciones. Por otro lado, en todos los casos se utilizó el modelo sin restricciones para obtener la información explicativa debido a que es el único que permite relaciones entre las variables de subsistencia (outputs) y las variables ecológicas (inputs).

Fase v. **Aplicación del modelo y obtención de los resultados:** como se ha mencionado en la sección 2.2, las redes bayesianas producen dos tipos de información:

- *Información explicativa:* a partir del cálculo de la fuerza de las relaciones con la **función arc.strength**, implementada en el paquete bnlearn, podemos calcular la fuerza de las relaciones entre los outputs y los inputs e identificar aquellas significativas en forma de p-valor. Además, las redes son ilustradas mediante grafos directos acíclicos donde se representan las relaciones y las distribuciones de las variables dentro del sistema. Es importante apuntar que esta información es solamente observable en los modelos ANB y el Modelo sin restricciones. En cambio, en el caso del modelo de NB, las relaciones entre inputs y entre outputs están restringidas y, en consecuencia, su gráfico no es informativo porque fuerza la relación bilineal entre cada output y cada input, aunque realmente no estén relacionadas o lo estén de forma no lineal.
- *Información predictiva:* a partir del modelo construido podemos predecir las clases de los outputs en función de los valores de los inputs. Por lo tanto, el modelo también puede ser utilizado para predecir escenarios que queramos conocer y no estén registraos en la base de datos que hemos empleado para crear el modelo.

3. RESULTADOS

En el proceso de validación de los resultados solamente se encontró un caso, cuando se predice la ganadería, en el que uno de los modelos, el NB tuviera una precisión superior a los otros modelos (p-valor: 0,03058). Únicamente en este caso se ha explorado con un modelo, en cambio, en todos los otros casos se han tenido en cuenta los tres modelos (NB, ANB y sin restricciones).

3.1. Información explicativa

En la **Tabla 4** se muestran las correlaciones positivas entre el tipo de subsistencia y el medio dónde viven las comunidades. Podemos observar un mayor número de correlaciones positivas en el modelo de NB, hecho que indica que cuando más complejo es el modelo porque más interrelaciones son permitidas, los outputs están menos determinados por los inputs. Por otro lado, las estrategias de subsistencia más correlacionadas con el medio son la ganadería, con la media y constancia de producción primaria neta del suelo y la precipitación media mensual, y la caza con la distancia a la costa y la constancia y contingencia de la producción primaria neta del suelo. Es así como se evidencia la relevancia de la productividad del suelo para definir la intensidad en la que se practican estas dos estrategias.

Output	Modelo	Relación significativa	p-value	
Ganadería	*NB*	Ganadería - Producción primaria neta media mensual	1,49E-02	*
	NB	Ganadería – Constancia en la producción primaria neta	2,15E-02	*
	ANB	Ganadería – Precipitación media mensual	4,53E-06	***
	ANB	Ganadería - Producción primaria neta media mensual	1,49E-02	*
	ANB	Ganadería - Constancia de la producción primaria neta	2,15E-02	*
Caza	*NB*	Caza – Distancia a la costa	2,15E-02	*
	NB	Caza - Constancia de la producción primaria neta	7,23E-03	**
	NB	Caza - Contingencia de la producción primaria neta	1,41E-04	***
Recolección	*NB*	Recolección – Constancia en la precipitación	9,66E-03	*
Agricultura Ganadería Caza Recolección Pesca	*Sin restricciones*	Ganadería – Agricultura	3,59E-11	***

Tabla 4. Relaciones significativas identificadas a partir de los tres modelos. Clasificación p-valores: 0.05-0.01=*; 0.01-0.001=**; <0.001=***. Fuente: Elaboración propia.

En cuanto a la interrelación entre las variables de subsistencia, la ganadería ejecuta la función de nexo entre el grupo caza – recolección, la agricultura y la pesca (**Figura 3**). Es interesante el hecho que la caza y la recolección están muy interrelacionadas entre ellas, así como la ganadería con la recolección. Por otro lado, las variables ecológicas también están fuertemente relacionadas entre ellas. De hecho, podemos dividirlas en dos grupos: variables topográficas y temperatura media (relación de elevación con la temperatura media, pendiente y distancia a la costa), variables del clima y productividad del suelo. Un aspecto interesante que destacar es el rol de la pesca en el modelo ya que conecta las variables de subsistencia con las del medio, aunque no se ha identificado ninguna relación estadísticamente significativa de la pesca con las otras variables. Una posible interpretación al rol de la pesca sería la propuesta en el estudio de Ahedo *et al*. (2021), dónde se argumenta que la pesca no está directamente determinada por el medio sino por las dinámicas internas de la comunidad como estrategia para diversificar los recursos cuando estos son limitados. Siguiendo esta explicación, la pesca estaría relacionada con las otras estrategias de subsistencia y entorno, pero no limitada por estas. No obstante, necesitaríamos más datos y evidencia para confirmar esta hipótesis.

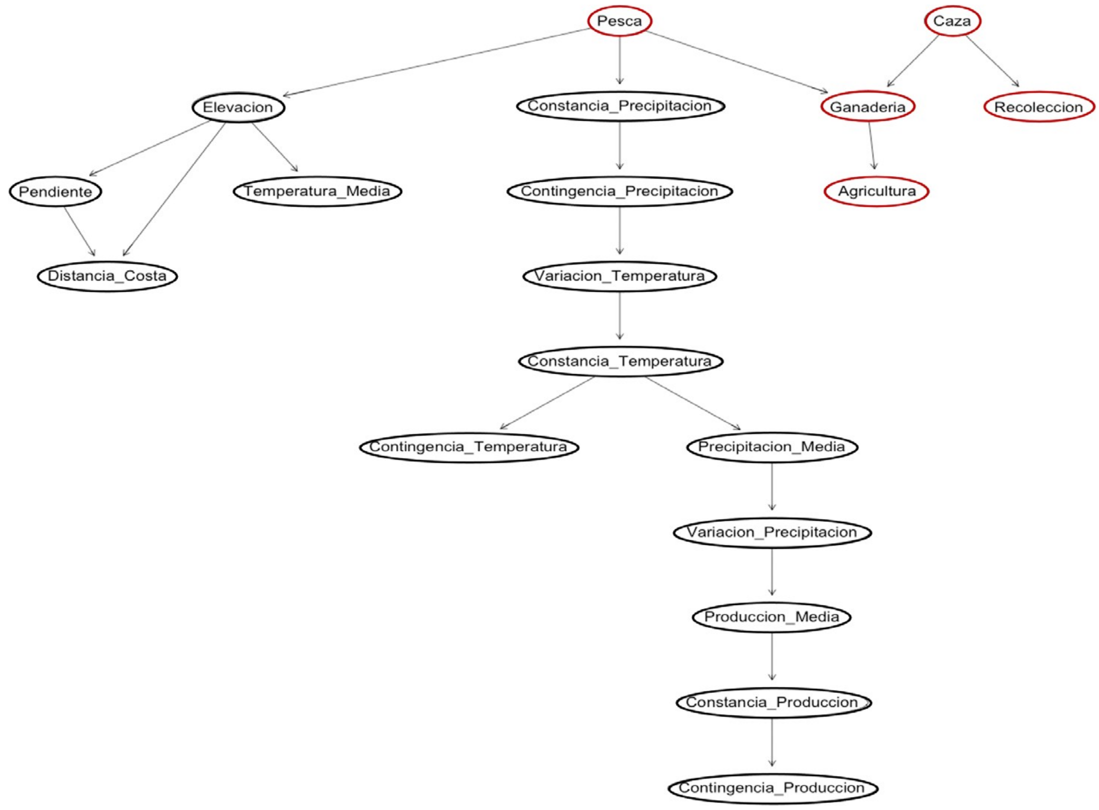

Figura 3. Modelo sin restricciones representando la relación entre el tipo de subsistencia (outputs, rojo) con las variables ecológicas (inputs, negro). Las flechas del modelo partende los outputs a los inputs porque el modelo está construido de manera que los valoresmás probables de los inputs se calculan a partir de los valores de los outputs. También sería posible aprender el modelo de los inputs a los outputs, hay diversos modos de construirlas redes y en este caso se ha optado por esta configuración. Fuente: Elaboración propia.

3.2. Información predictiva

Para explorar en más detalle hasta qué punto las variables ecológicas definen el tipo de subsistencia de las sociedades analizadas, se han hecho dos predicciones de tres contextos ambientales diferentes con valores completamente contrarios: contexto con valores mínimos, medios y máximos (definidos en la **Tabla 5**). El objetivo de este ejercicio de predicción era explorar hasta qué punto las variables el medio determinen el tipo de estrategias económicas de las comunidades estudiadas.

Outputs	Inputs	Contexto 1	Contexto 2	Contexto 3
Agricultura	Distancia a la costa	<140	140-600	>=600
Ganadería	Elevación	<300	300-800	>=800
Caza	Pendiente	<0,75	0,75-2,5	>=2,5
Recolección	Temperatura media anual	<5	5-20	>=20
Pesca	Variación de la temperatura media	<1,3	1,3-20	>=20
	Constancia de la temperatura	<0,5	0,5-0,7	>=0,7
	Contingencia de la temperatura	<0,12	0,12-0,2	>=0,2
	Precipitación media mensual	<1,06e+05	1,06e+05-1,67e+05	>=1,67e+05
	Variación de la precipitación media	<7,86e+09	7,86e+09-1,49e+10	>=1,49e+10
	Constancia de la precipitación	<0,4	0,4-0,5	>=0,5
	Contingencia de la precipitación	<0,2	0,2-0,3	>=0,3
	Producción primaria neta media mensual	<1	1-3	>=3
	Constancia de la producción primaria neta	<0,2	0,2-0,3	>=0,3
	Contingencia de la producción primaria neta	<0,2	0,2-0,3	>=0,3

Tabla 5. Definición de los contextos para predecir el tipo de intensidad de estrategias de subsistencia. En el contexto 1, los inputs tienen los valores mínimos, en el 2 los valores medios y en el 3 los máximos. Fuente: Elaboración propia.

Los resultados están definidos en la **Tabla 6** y podemos observar el mismo resultado para los contextos de valores mínimos y medios de las variables del ambiente: las comunidades basaran entre el 46-75% de su dieta en la agricultura y complementaran su dieta con las otras estrategias (con intensidades inferiores al 15%). En cambio, cuando los valores de todas las variables ecológicas tienen valores máximos, la agricultura seguirá siendo practicada con una intensidad entre el 46-75%, pero en lugar de tener una dieta mixta con otras estrategias, se consumirán los recursos ganaderos con más intensidad (entre el 16-45%).

Contextos	Subsistencia	Modelo Naïve Bayes		Modelo Augmented Naïve Bayes		Modelo sin restricciones	
		Predicción	*Nivel de confianza*	*Predicción*	*Nivel de confianza*	*Predicción*	*Nivel de confianza*
Contexto 1	*Agricultura*	45-75	0,82381	45-75	0,82015	45-75	0,75252
	Ganadería	<15	0,83324	<15	0,76175	<15	0,61077
	Caza	<15	0,77294	<15	0,78386	<15	0,76981
	Recolección	<15	0,87198	<15	0,87556	<15	0,89811
	Pesca	<15	0,53892	<15	0,51947	<15	0,6415
Contexto 2	*Agricultura*	45-75	0,77688	45-75	0,75084	45-75	0,74809
	Ganadería	15-45	0,58672	15-45	0,54897	<15	0,58035
	Caza	<15	0,80788	<15	0,81424	<15	0,76981
	Recolección	<15	0,92169	<15	0,92555	<15	0,89811
	Pesca	<15	0,83286	<15	0,8624	<15	0,72968
Contexto 3	*Agricultura*	45-75	0,6219	45-75	0,62195	45-75	0,74817
	Ganadería	15-45	0,39024	15-45	0,39024	<15	0,58089
	Caza	<15	0,82927	<15	0,84139	<15	0,76981
	Recolección	<15	0,89024	<15	0,89922	<15	0,89811
	Pesca	<15	0,80488	<15	0,80271	<15	0,72813

Tabla 6. Resultados de las predicciones. Fuente: Elaboración propia.

4. DISCUSIÓN Y CONCLUSIONES

Al inicio de este estudio, nos planteábamos **caracterizar la aplicación de la metodología de aprendizaje automático en Arqueología en general y, más específicamente, en el ámbito de estudio de sistemas socioecológicos**. A través del análisis bibliométrico de los artículos publicados empleando AA en Arqueología, se ha comprobado que realmente esta metodología ha empezado a aplicarse de manera más consistente a partir del 2019. Identificar el/los motivo/s por los cuales esta metodología se ha vuelto más común requiere un estudio en más profundidad de este fenómeno metodológico, dónde se contraste el número de artículos publicados en AA con otras metodologías computacionales, por ejemplo. No obstante, podría ser debido a las potencialidades del método, de predecir información desconocida, que puede ser muy atractivo en el ámbito arqueológico a causa de las propias limitaciones del registro. También podría ser por la democratización de los datos que se ha dado en los últimos años, dónde se está volviendo una práctica común publicar en abierto los datos arqueológicos para poder reutilizar estos datos en otras investigaciones, como, por ejemplo, se ha hecho en este estudio con los datos etnográficos recogidos de una base de datos en abierto. Esta práctica de 'reciclaje' favorece al desarrollo de estudios con dimensionalidad macro, más allá de la dimensionalidad de un asentamiento (ej., VanValkenburgh y Dufton, 2020; Huggett, 2018).

Al inicio de este estudio, se planteaba que no había demasiados estudios de AA ni se había explorado su aplicabilidad en la ciencia arqueológica. Así mismo, en esta investigación se ha evidenciado que esta metodología aún se encuentra en su primera fase de aplicación, se ha implementado para explorar diversos casos de estudio, cuestiones y tipo de materiales, pero aún no se ha hecho el esfuerzo de integrarla como una metodología más como sí que se ha dado con otros métodos computacionales como la simulación, por ejemplo. Actualmente, nos encontramos en un estadio de aplicación del método, con mucha diversidad de aplicaciones y técnicas, pero aún no ha habido un diálogo y discusión sobre como AA se puede integrar en los estudios arqueológicos.

En este contexto, en el ámbito espacial sí que parece que se empieza a consolidar la práctica de combinar métodos propios de GIS con algoritmos AA, sobre todo de *deep learning*. Sin embargo, no parece que la elección de algoritmo esté relacionada con el tipo de datos, sino que hay tendencia en los ámbitos de emplear reiteradamente el mismo tipo de algoritmo. En cambio, en el ámbito de estudio de sistemas socioecológicos y de dinámicas sociales, hay una gran diversidad de algoritmos empleados y también se ha observado que en algunos casos los modelos se utilizan para conceptualizar los sistemas desde el conocimiento experto (ej., Barceló, 2008). Este aspecto es sobre todo patente en el caso de las redes Bayesianas con el algoritmo de NB. Estas tendencias pueden ser debidas a las propias tradiciones de investigación que hay en cada ámbito y sería interesante explorar en el futuro otras combinaciones de métodos que podrían ser perfectamente complementarias, como serían los métodos de AA y la simulación.

Por otro lado, el presente estudio también pretendía **definir los beneficios y limitaciones de AA para el estudio de sistemas socioecológicos** en arqueología mediante su aplicación de un caso concreto. En el caso de estudio se ha modelado un sistema social y económico complejo teniendo en cuenta las características ecológicas de su ubicación. A partir de los resultados, se ha observado la existencia de estrategias de subsistencia, sobre todo la agricultura, ganadería y la caza, que están influenciadas por algunas variables ecológicas, especialmente por el clima. En este sentido, se han obtenido resultados inesperados como el hecho que la productividad del suelo determina en mayor medida la intensidad que se practica la ganadería que la agricultura, contrariamente a lo sugerido en otros estudios (Nendel *et al.,* 2011; van Ittersum *et al*., 2008). Siguiendo a Palacios *et al.* (2022), la reducida importancia de la productividad del suelo en la agricultura estaría relacionada con la fuerza de trabajo, organización social y desarrollo tecnológico, aspectos que compensarían una baja productividad.

Mediante las redes bayesianas se ha modelado el sistema investigado de forma compleja y no-linear, cuantificando las relaciones más significativas entre variables y prediciendo hipotéticos escenarios. No obstante, es importante matizar hasta qué punto estos resultados son fiables. Con respecto a la validez del modelo, este se ha validado y cuantificado su precisión, pero, el modelo es tan bueno como lo son sus datos. En la recogida de datos, el/la investigador/a recopila aquellos que considera que son importantes, los procesa y categoriza (según el algoritmo empleado). En función de la agrupación de clases que se realice, los resultados pueden variar y, por lo tanto, son decisiones que el/la investigador/a toman y que determinan el resultado. Así mismo, los modelos se construyen a partir de los datos, pero también están modelados por restricciones que se determinan durante el diseño del modelo en función del tipo de estructura, cómo se ha detallado en la sección 2.3. con la construcción de tres modelos de redes bayesianas diferentes.

Por otro lado, cabe mencionar que en los modelos de AA identificamos patrones, las tendencias a partir de los datos conocidos. Los *outliers* o valores menos comunes del sistema no se pueden identificar en el modelo y otros métodos computacionales como la simulación, por ejemplo, serían más apropiados. En esta misma línea, los modelos AA son potentes a nivel predictivo, pero a nivel explicativo son difíciles de interpretar y es necesario contextualizar los resultados a partir de una aproximación teórica. Cabe destacar que esta limitación es compartida con otros métodos cuantitativos, puesto que estamos calculando las relaciones entre las variables. Es por este motivo que una opción para superar esta limitación sería combinar AA con modelos computacionales, por ejemplo. Sería interesante combinar el AA con otras metodologías como las computacionales para contrastar los resultados y enriquecerlos a nivel explicativo; concretamente, con el modelo basado en agentes, tiene un gran potencial a nivel explicativo y desarrollo de hipótesis que sería muy positivo en este caso para comprender los resultados que se han obtenido. No obstante, a partir del análisis de la trayectoria de AA en arqueología, hemos constatado que cuando se combinan métodos, suele ser entre diferentes algoritmos de AA o con GIS, pero no con modelos computacionales. A partir del estudio realizado, se podría explorar la utilidad de complementar los diferentes métodos y, en el futuro, sería interesante contrastar los resultados que hemos obtenido en la presente contribución desarrollando un modelo basado en agentes que explore la relación entre las variables ecológicas y el tipo de subsistencia de las comunidades agroganaderas para obtener información que nos ayude a interpretar los resultados obtenidos.

Para concluir este artículo, nos volvemos a plantear, ¿se ha producido en Arqueología un cambio de paradigma con la aplicación del aprendizaje automático? Podemos decir que todavía no. La eclosión de esta metodología es muy reciente, su aplicación muy diversa y aún su aplicación no está sistematizada. De hecho, la mayoría de las veces se utiliza como un método computacional para producir modelos predictivos, pero la singularidad del método, que sería su construcción a partir de los datos, aún no es una práctica recurrente en la ciencia arqueológica.

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Chapter 2

Towards Agropastoralism

2.1. Emergence of Mixed Economies

It is generally accepted that we can situate the '*when*' and '*where*' of the emergence of agropastoralism approximately ~10,000 years ago at southwestern Asia (Hancock, 2022; Iob & Botigué, 2022). This 'core area' has been traditionally called the Fertile Crescent (Breasted, 1916) or the Near East, but these terms are derived from artificial designations or does not englobe the whole territory and lead to a potential 'Levantine bias'. This region will be termed southwestern Asia henceforth as some authors suggest (Barker, 2006:105). This chronology is analogous to a period of instability during the Last Glacial Maximum (from c. 22,9-18,9 to 15 ka cal. BP), the end of the last ice age and the onset of the current interglacial period (Blockley & Pinhasi, 2011:103). Known as the *Bølling- Allerød interstadial period* (c. 14,9-12,9 ka cal. BP), warmer, milder, and more humid environmental conditions were present and culminated in the Younger Dryas Stadial (c. 12,9-11,7 ka cal. BP). This period was followed by a transition into warmer climatic conditions during the Holocene (from c. 11,7-10,5 ka cal. BP) (Bar-Matthews et al., 2000, 2003) were also relevant climate phenomena known as the 9,2 and 8,2 ka events took place (Rasmussen et al., 2007, 2014; Alley & Agústsdottir, 2005; Steffensen et al., 2008). It is in this last event in which the earliest evidence of agropastoralism is found.

It was not a sudden event; it was predated by a long period towards plant and animal domestication which begun approximately c. 23 ka cal. BP ('Epipalaeolithic') in the southern Levant. This process is documented by the remains of wild barley, wild wheat, and harvesting tools (Piperino et al., 2004) in Ohalo II settlement (Israel), dated between 22,5 and 23,5 ka cal. BP (Weiss et al., 2004, 2008, 2011). Ohalo II was not isolated, similar remains have been found in other settlements such Kharanaeh IV or Jilat VI), and they are also related to other smaller sites which has been interpreted as potential networks among populations (Goring-Morris & Belfer-Cohen, 2011). Additionally, potential exchange networks are suggested from the evidence found of the marine mollusc assemblage from the Sinai (Bar-Yosef & Killebrew, 1984). The settlements mentioned in this chapter are depicted in **Figure 3**.

Figure 3. Map of the settlements mentioned in Chapter 2.1. 1. Abu Hureyra; 2. Ain el Kerkh; 3. Ain Ghazal; 4. Ain Mallaha; 5. Akarçay; 6. Beidha; 7. Bouqras; 8. el-Wad Terrace; 9. Göbekli Tepe; 10. Hayonim grave VII; 11. Hilazon Tachtit; 12. Jerf el-Ahmar; 13. Jericho; 14. Jilat VI; 15. Kharnaeh IV; 16. M'lefaat; 17. Mureybet; 18. Netiv Hagdud; 19. Ohalo II; 20. Qermez Dere. 21. Raqefet cave; 22. Sabi Abyad; 23. Tell Halula; 24. Wadi Hammeh 27.

2.1.1. Proto-Agropastoral Systems

Although these early agropastoral communities probably practiced some degree of sedentarism, the first recognised evidence is found by the late Epipalaeolithic, during the Bølling-Allerød interstadial period. The Bølling- Allerød interstadial period was characterised by a favourable and warm climatic condition in which park woodland expanded from the Southern Levant out over the uplands and steppes of the northern Fertile. These early sedentary communities are so-called Natufian, and they are divided into two periods: *Early Natufian* (c. 15-13,8 ka cal. BP) and *Late Natufian* (c. 13,8 – 11,5 ka cal. BP) (Garrod & Bate, 1937; Garrod, 1957; Perrot, 1966; Bar-Yosef, 1998; Belfer-Cohen & Bar-Yosef, 2000; Munro, 2004; Belfer-Cohen & Goring Morris, 2005). The principal difference between these two phases is the intensity in which they consumed agropastoral resources.

Natufian communities lived in large open-air camps and caves in the Zagros area specially, the Levantine corridor close to the water. With a higher density on sites compared to previous settlements, a diversity of site patterns emerged: some groups continued being organised in small-scale communities composed by nuclear households, whereas others were large-extended with a more communal internal organisation as suggested in Wadi Hammeh 27 and el-Wad Terrace sites (e.g., Goring-Morris, 1996; Goring-Morris & Belfer-Cohen, 2008).

During the Early Natufian, communities practiced a seasonal pattern of mobility in which they adapted their food consumption depending on climatic conditions. Because of chronological difficulties, it is still unsure the intensity in which farming resources were consumed but it is thought that it would have been significant for the grinding equipment for milling and pounding and storage bins (Arranz-Otaegui et al., 2016; Ibáñez et al., 2019:228). Conversely, during the Late Natufian, there is evidence for farming intensification. They extended their cultivation area in the surroundings of their sites (as documented in Mureybet) (Willcox et al., 2008; Ibáñez et al., 2016), focusing on cultivating specific species (horticulture). Resources were produced and consumed more intensively, suggesting a potential specialisation on cereals. Cereals, legumes, weeds, fruits (Arranz-Otaegui et al., 2018; Belli et al., 2023; Rosenberg & Chasan, 2021), wild animals (Bridault & Rabinovich, 2019) and fish (Munro et al., 2021) were consumed, shaping a broad-spectrum diet in which diversification had a relevant role. For example, the Abu Hureyra site (13 to 12 ka cal. BP) was only occupied from early spring to late autumn, period in which its population hunted gazelle, gathered wild fruit such as pistachio and farmed einkorn, rye, and pulses (Colledge & Conolly, 2010; Legge & Rowley-Conwy, 2000).

Concerning burial practices, we also identify some differences. In Early Natufian, burials are found in caves (e.g., Raqefet Cave; Lengyel & Bocquentin, 2005) and houses (e.g., Ain Mallaha; Valla et al., 2017). Despite individual burials are dominant in the archaeological record, the first evidence of collective graves is observed, with multiple burials including simultaneous inhumations (Ibáñez et al., 2019: 239). They are thought to be family burials (e.g., Hayonim Grave VII; Belfer-Cohen, 1988) and they present a great variability in the people buried (mixed sexes, ages, burial typology). Additionally, a unique type of burials has been recovered at Hilazon Tachtit (Grosman et al., 2008) and Grave X at Ain Mallaha (Perrot et al., 1988) where both human and dog were buried together (they are also known as the 'shaman' burial and the 'gazelle-horned' burial, respectively).

During the Late Natufian, on the other hand, we observe the beginning of mortuary customs that persisted during the PPN, such as the separation of the head from the rest of the body in some human skeletons (skull caches) (Goring-Morris & Belfer-Cohen, 2013). This practice is believed to be linked to the 'cult of ancestors', where the whole community participated, propitiating the cohesion among the settlement inhabitants.

Throughout the Natufian period, exchange activities intensified. Intra-settlement exchange networks distributed valuable materials such as obsidian, shell, basalt, oche or coloured stones and tools like basalt grindstones (Weinstein-Evron, 1991, Weinstein-Evron et al., 2001; Delage, 2018; Rosenberg et al., 2020). Long-distance exchange networks from the Mediterranean or the Red Sea in the Natufian sites in Southern Levant (in a distance between 50 and 300 kilometres from sites) also played a relevant role. Exotic items such as stone vessels, beads, decorated bone tools and grindstone utensils were traded. They are interpreted as a potential interest of Natufian communities for foreign objects as a tool for social distinction. However, it remains uncertain whether they aimed to define themselves at an individual-level or these objects were acquired/ manipulated to construct an identity at a community-level.

2.1.2. Consolidating Agropastoral Communities

At the beginning of the Holocene (c. 11,7 to 10,5 ka cal. BP), environmental conditions changed again, and temperatures raise and maintained through a long period of time. Chronologically, the improvement of the climate was simultaneous to the emergence to the first considered 'agropastoral' communities. They are known as "aceramics" because there is no evidence that they produced ceramics but clay figures and the period that the communities with these characteristics are present, is divided into two cultural phases: the *Pre-pottery Neolithic A* (PPNA) and the *Pre-pottery Neolithic B* (PPNB) (Kenyon, 1957). The PPN period is considered when the sedentarism and the domestication of animals and plants were fully established, consolidating preceding socioeconomic changes of Natufian.

The PPNA was a brief phenomenon which lasted about a thousand years (c. 11,7 to 10,5 ka cal. BP). It has traditionally been divided into three different cultural entities, the Khiamian, Mureybetian, and Sultanian (Cauvin, 2000a) which cover the territory of the southern-central Levant (e.g., Weiss et al., 2006; White & Makarewicz, 2012), the Euphrates area (e.g., Willcox et al., 2008) and the Zagros (e.g., Riehl et al., 2013). Other social groups were those who remained sedentary hunter-gatherers along the Tigris River valley or as mobile populations in the semi-arid lands of the eastern and southern Levant (Goring-Morris, 1993; Goring- Morris & Belfer-Cohen, 1997; Bar-Yosef & Kislev, 2014).

Generally, it is estimated that PPNA population was denser in comparison to the Late Natufian communities (Kuijt & Goring-Morris, 2002). Located in the Levantine corridor, their sites ranged in very different sizes: from small surfaces scatters (c. 100 - 150 m2), medium sizes settlements (c. 2,000-3,000 m2) and few larger ones (2-3 hectares) with architectural remains.

Settlements consisted in encampments of small circular semi-subterranean structures (3-6 meters in diameter) with hearths, pits, activity areas, plastered floors (Goring-Morris & Belfer-Cohen, 2013). It is thought that these households would have been inhabited by large extended families (Flannery, 1972).

It is particularly interesting the presence of differences between the southern and the northern Levant in terms of construction and social organisation. Southern communities maintained a more nuclear household organised along kinship lines (Belfer-Cohen & Goring-Morris, 2011: 213), like the Natufian record and with some shared spaces. A good example is Jericho, with numerous silos to supply the population and walls and tower, although it is unclear whether it was built to defend the site against people, or flooding, or both (Bar-Yosef & Belfer-Cohen, 1992). On the other hand, in the north semi-subterranean structures interpreted as ritual are found in Jerf el-Ahmar or Mureybet (Stordeur, 2019; Stordeur et al., 2000) and this cult is believed that developed towards the emergence of supra-regional ritual sites such as Göbekli Tepe (Schmidt, 2010). These new types of sites in the northern Levant probably needed a massive investment of labour force, resources, and people. They are believed that they were built as social pillars of interaction between different communities throughout the region, which particularly differs compared to the south, where ritual behaviours were in private-level (Belfer-Cohen & Goring-Morris, 2011: 214).

In the PPNA register can be observed as a preference for juvenile specimens, which has been interpreted as some sort of 'proto-herding' by selecting young animals to tame them. This model of specialised hunting and control of the wild (Vigne, 2017) it is proposed for goats (Hole, 1996) and wild boar (Redding, 2005). The consumption of crops was equally relevant in PPNA settlements, along with gathering foodstuffs such as seeds and fruits (Barker, 2006: 134). Thus far, it is uncertain whether plants were just harvested or husbanded. It is believed that it was the time of systematic experimentation in cultivation and intensification of harvesting of natural fields, which is called 'pre-domestication cultivation' (Colledge, 2002). The first evidence of plant domestication is found at some archaeological sites such as Jericho, Netiv Hagdud, Mureybet, Jerf el-Ahmar, Qermez Dere, and M'lefaat.

By the end of PPNA, a suite of plants was already partially domesticated as the frequencies of wild forms gradually diminished in the fields documented (Bar-Yousef, 2017: 69). Probably, from the start of wild plants cultivation until the development of domestic species, a span of 1,000-1,500 years was necessary (Ibáñez et al., 2019). Be that as it may, during the PPNA first experiences with control of wild plants and animals took place, and that likely led to new forms of organisation to produce foodstuffs to maintain the whole settlement community. The first visible signs of domesticated plants are dated at this time, spikelet forks of emmer and einkorn wheat with tell-tale and rough disarticulation scars provide the most conclusive evidence that cereals were domesticated at this time. It is believed that was the time when the population divided into food-producers and non-producers, the latter would be individuals specialised in crafts, for instance. There is still a debate, however, addressing the question of whether agriculture was originated only in this area (Lev-Yadun et al., 2000) or across a broad area which would include the Levant and northern Fertile Crescent (i.e., Weiss et al., 2006).

There was presumably a more structured exchange network of exotic items which lead to the interaction among various communities during this phase, as demonstrated with mitochondrial DNA studies. The movement of people has been regarded as a key mechanism for relaxing group tensions and to share novel experiences implemented by communities, which prevented the risks of involution (Ibáñez et al., 2016). It is noteworthy the case of Cyprus, where the introduction of wild boar took place approximately 11,4 ka cal. BP by foragers that emigrated to the island (Vigne et al., 2011). Mitochondrial DNA analyses indicate that pioneering groups regularly visited the island from the 12,9 ka cal. BP (Manning et al., 2010) and groups coming from southwest Asia continued migrating to the island until the 11,950 BP taking with them the cultural novelties associated with the emergence of the Neolithic, including plants and animals in the process of domestication (Ibáñez et al., 2019).

Another continuing practice with Natufian roots was the separation of the skull from some buried individuals. This procedure is frequently recovered in PPNA settlements, and it is grasped as some sort of ancestor worship (Bar-Yosef, 1998; Cauvin 1978, 1985; Kuijt, 1995, 2000; Le Mort, 1992; Stordeur & Abbes, 2002; Verhoeven, 2004). Multiple burials became more frequent, and, in some cases, they looked more like trash pits with human remains rather than venerable graves (Ibáñez et al., 2019: 240). Burials predominantly had scarce grave goods and, the few that may have, researchers encountered the difficulty of discerning whether faunal remains were belongings or ceremonial feasting. This is interpreted as the result of population growth associated with full-scale agriculture and animal husbandry in the Levant and the emergence of the first evidence of social inequality (Kuijt, 2000).

The beginning of the PPNB phase is dated approximately by 10,5 ka cal. BP. This phase is divided into three distinct periods: (i) Early PPNB c. 10,5 - 10,2 ka cal. BP; (ii) Middle PPNB c. 10,2 - 9,5 ka cal. BP and (iii) Late PPNB c. 9,5 - 8,4 ka cal. BP. During the early PPNB, several processes that had begun during the PPNA materialised: animal and plants were fully domesticated, and the staple foodstuffs and settlements were permanent, larger, and made by more durable materials (i.e., stone foundations, mudbrick, and pisé walls) (Barker, 2006: 137).

Settlements were situated in low-lying locations near to water supplies and alluvial soils (Sherrat, 1980). Settlements expanded and first rectangular household structures were constructed. Built with sun-dried mudbricks, they had above-ground features (e.g., clay silos, bins), below-ground structures (e.g., pits) for storing food (Kuijt, 2015). Changes in household shape and storage facilities have been associated with a replacement of group-oriented strategies practised by communities organised in large extended groups for a more family-oriented strategy in which the nuclear family has its own private storage (Flannery, 2002). Despite the presence of storage facilities, it is also questioned the capacity of PPN households to be self-sufficient as supra-household cooperation in farming communities is crucial to diminish the survival risk (Bogaard, 2017). Nevertheless, cooperation is difficult to identify empirically (Enloe, 2003; Finlayson, 2020). Another aspect to consider is that rectangular households could also have been inhabited by extended families (Goring-Morris & Belfer-Cohen, 2008) and some researchers, even question whether the social organisation of these communities could be identified with the current evidence (see Banning & Chazan, 2006; Saidel, 1993).

Another major change is first clay artefacts are recovered in form of figurine (Ibáñez et al., 2019: 227). While their diet was based on ground cereals, foraging practices prevailed. Based on the recovered evidence of PPNB settlements that the so-called "founder crops" were defined: emmer wheat, einkorn wheat, barley, lentil*,* pea, bitter vetch, chickpea, and flax (Abbo et al., 2013). However, recent studies propose the addition of further species into this package of grass pea (despite the bulk of its early remains comes from 8th-7th millennia BP in Greece and Bulgaria), rye (few remains), and fava bean (no compelling evidence). It is believed that the PPNB population cultivated several crops in the same fields, and they selected these species because they were more suitable for the cooler and humid environment of Southwest Asia (Harlan, 1998; Willcox, 1996; Araus et al., 2007). Animal herding was extended to further animal species compared to the PPNA. Sheep, cattle, goats, and pigs are found in the Zagros and Taurus regions by the onset of the PPNB (Uerpmann, 1996; Vigne et al., 2011; Zeder, 2012).

Concerning social practices, obsidian exchange networks were maintained (Ortega et al., 2014) and burial practices. There was a continuity of Natufian and PPNA phases such as the removal and reburial of skulls (some of them plastered and painted) in the southern Levant or the appearance of proper "houses of dead" in the northern Levant (Guerrero et al., 2008: 59). While PPNA sites like Göbekli Tepe were apparently used for ritual purpose, there is a return to the practices in individual-level which can be seen as a disintegration of the previous large-scale social structure organisation.

Sedentary agropastoral societies started to expand throughout the territory, and it is believed that the people who were still living as foragers came under pressure either to move away or to intensify their subsistence base by adopting components of the agriculture system that best suited their seasonal behaviour, such as herding of sheep, goat, cattle, and pigs. The diversity in available foodstuff led to the presence of social differentiation in terms of resource accessibility. It is recorded in this period disparate diets which suggest various dynamics. The introduction of herding has also been associated with a change in dietary practices: sheep and goats could additionally be used for milk and secondary products like cheese so ceramic containers were required to produce these more-sophisticated foodstuffs.

The period comprised c. 10,2 - 9,8 ka cal. BP (Middle PPNB) is poorly represented in the archaeological record and that has been linked to a potential population decrease as settlements such as Mureybet, Jerf el Ahmar or Göbekli Tepe were abandoned around c. 10 ka cal. BP. On the other hand, it has been recovered several newly founded settlements in this region around 9,8 ka cal. BP: Akarçay, Sabi Abyad, Tell Halula, Abu Hureyra or Bouqras (Borrell et al., 2015: 4). Except for Ain el Kerkh site, the locations of the new settlements did not coincide to previous settlements, which has been viewed as new settlers would have prevented them strategically. The transition to a full agropastoralism economy depending on domesticated-type species occurred between 10 - 9,8 ka cal. BP (Borrell et al., 2015: 11) as the latter group of settlements represent a new economic system.

During the Late PPNB (c. 9,5 - 8,4 ka cal. BP) there was the emergence of the 'mega-site' village phenomenon which doubled and tripled PPNA sites (Kuijt, 2000). Novel forms of individual representation were available by using stone masks and plastered skulls and ritual-related such as trophies to gods. Following the previous Natufian tradition, separate areas for communal and cultic purposes were maintained such as Beidha or 'Ain Ghazal (e.g., Rollefson, 2000). The already existing mortuary customs were intensified during this period (Belfer-Cohen & Goring-Morris, 2011: 214).

The Late Phase of the PPNB has received special interested in research as it is associated with major climatic events: the 9,2 and 8,2 ka events. The 9,2 ka event occurred around 9,3-9,2 ka BP (estimated from Greenland ice cores with an estimated maximum counting error of 70 years; Rasmussen et al., 2007, 2014) and was caused by meltwater escaped from Lake Agassiz which caused an impact on a global climate including in Greenland, Alaska, Europe, the Arabian Peninsula and China, with a duration between 40 and 100 years. Although it probably had severe consequences as it produced a drop of temperatures, it is believed that it was of lower magnitude compared to the 8,2 ka event (Flohr et al., 2016). For the 9,2 ka event, it is suggested that people emigrated into the desert (Kuijt & Goring-Morris, 2002) but this occurred before this event (Flohr et al., 2016: 32). A recent examination of 14C-dates evidence points that there is not currently enough evidence for any site being abandoned over this period and sites that potentially reduced its population, they were not located in extreme climatic conditions as it would be expected (Flohr et al., 2016).

On the other hand, the 8,2 ka event dates around c. 8,2-8 ka cal. BP (Alley et al., 1997) and it lasted around 160 years (Van Der Plicht et al., 2011). According to proxy data, the 8,2 ka event caused extremely cold temperatures and arid conditions throughout the Northern Hemisphere (e.g., Alley & Agústsdottir, 2005; Bar-Matthews et al., 2003). It brought cold and dry conditions to some Northern Hemisphere regions in response to a very large outburst flood that cooled the North Atlantic region (Alley et al., 1997; Alley & Agustsdottir, 2005). Greenland ice core records reveal that temperatures in the North Atlantic region decreased abruptly (Weninger et al., 2006: 401), leading to massive floods in coastal regions (Renssen et al., 2001, 2002). In southwestern Asia, there was a reduction in annual precipitation of the Dead Sea (Bar-Yosef, 2017: 69; Weninger et al., 2009; Litt et al., 2012), an increment in aridity in the territory and it is thought that these unsuitable conditions favoured the movement of people to other territories with a more proper environment. It is believed that in southwestern Asia caused the abandonment of "mega-sites" (Staubwasser & Weiss, 2006). For example, prior literature has emphasised especially the consequences that this event caused in Catalhöyük site, where the East mound was supposedly abandoned abruptly at that time and after that, inhabitants developed a new settlement approximately 200 meters from the old location (Hodder, 2007; Biehl et al., 2012). However, other studies (Flohr et al., 2016) provide new insights into the interpretation of Çatalhöyuk East: while there are different levels VI and before with less densely packed occupation and more open spaces, less continuity in building and more focus in individual households, these changes occurred around 8,4 ka cal. BP (Cessford & Carter, 2005). On the other hand, a shift from the east to the west mound took place, but it did not happen before 8 ka cal. BP, potentially overlapping with the last occupation on the east mound (Flohr et al., 2016: 34).

Therefore, our current understanding of the 8,2 ka event and its consequences is far from complete. While some authors suggest that this phenomenon caused profound changes (e.g., expansion towards Europe; Weninger et al., 2006; the intensification of pastoralism; Migowski et al., 2006), others argue instead that PPNB communities could have been resilient to change as they would have already overcome prior climatic events (e.g., Flohr et al., 2016). It is also believed that the population decrease, and settlement abandonment could have also been due to a general socioeconomic and cultural collapse of the PPNB as if it was a bottleneck (Belfer-Cohen & Goring-Morris, 2011).

2.2. Modelling the Domestication Process

The domestication process has been extensively explored in relation to genetic modification (e.g., Allaby et al., 2018), the context and chronology of changes (e.g., Allaby et al., 2022; Purugganan and Fuller, 2011) and modification practices (e.g., Terrell et al., 2003; Bogaard et al., 2021). Despite there is still a vibrant discussion about potential domestication processes (e.g., Fuller et al., 2022), the concept of co-evolutional seems to have played a crucial role (Darlington, 1969). This process was divided for the first time by Rindos (1984) into three principal phases of varying the intensity between animals/plants and people and summarised in **Table 2**:

Phases	Actions	Plant responses
Incidental domestication	Humans simply harvest and disperse the propagules creating coevolutionary relationships with the plants. In the long run, that results in morphological changes in the plants.	Certain morphological traits are favoured, and domestication can intensify.
Specialized domestication (labelled to agroecology, Rindos, 1984)	Plants become an increasingly important part of man's immediate environment and are increasingly subject to protection. Habitat changes.	Genetic transformation in selected plants that are to provide the basis for the agricultural domestication.
Agricultural domestication	Final stage, plants are completely domesticated (morphologically and genetically) and they require human's control to survive.	Plants are completely transformed despite it must also consider that it may not be 'the final product' because plants may keep evolving.

Table 2. Rindos proposed classifying agriculture into three different phases of human-plant relationships (Rindos, 1984).

According to Rindos, to get to the point of domesticating a plant or animal, it was necessary to deliberately select those species to meet their cultural needs. By considering these phases on human control over plants, he formulated a mechanistic model dealing with means, processes and results that the origins of agriculture should be found in the shift from incidental and specialised and agricultural domestication (Yarnell, 1985: 698; Hardesty, 1985). The resulting model proposed that such changes in the subsistence system were the unintentional result of producing and consuming more proto-domestic resources (**4**):

$$W_t^* = W_t/\theta = \mu_t^* = \frac{D_t^*}{W_t^* + D_t^*} \quad \textbf{(4)}$$

Where:

W: foraging resources

D: domesticated resources

*: preference variability
θ: reduction of W as subsistence strategy
μ: relative frequency of D on diet
t: specific time

Following this formula, the effect of θ in the diet is an increment of the μ_t^* of D adopting the strategy of W^*. However, Rindos also considered that D could not be consumed indefinitely, but there is a variability U, which restricts the capacity of μ_t (**5**):

$$U = \frac{D + W^t}{D + W} \quad \textbf{(5)}$$

And the availability of resources would also be dependent on the number of population, the carrying capacity (**6**):

$$\frac{1}{N}\frac{dN}{dt} = d(\frac{Fmax - F}{F}) \qquad \textbf{(6)}$$

Where:
N: population
F: index of utilisation of food per capita
$Fmax$: maximum index of utilisation of food

Rindos model implied a fast and deliberate development of the origin of farming, which probably was not accurate since it is difficult to imagine that agropastoral communities knew the consequences of favouring some resources over others in advance. Despite this assumption, Rindos model represented a first step to model the conditions necessary for plants and animals' domestication and its amplification and dispersal. To address this assumption, Chu and Xu (2022) developed a Malthusian model (based on Locay, 1989; Baker, 2008) representing the transition from foraging to farming economies but considering the importance of human agency in form on labour. The model considers that all agents N are the same and each of them has l units of labour, which can be allocated to hunting-gathering (l_H) or farming (l_F) in a fixed amount of land Z. In case of farming, the fixed ratio of land given to farming labour is ρ, measured as $z = pl_F$. Each economic activity has a level of productivity (θ for hunting-gathering and φ for farming) and intensity (γ for hunting-gathering and $\alpha$for farming). Then, we can measure how many units of hunting-gathering food production h receives the agent that contributes l_H (**7**):

$$h = \frac{l_H}{l_H N}\theta(\bar{l}_H N)^{\gamma}(Z_H)^{1-\gamma} \qquad \textbf{(7)}$$

And the number of units of farming production *f* for an agent that contributes l_F (**8**):

$$f = \varphi(l_F)^{\alpha}(z^{1-\alpha}) \qquad \textbf{(8)}$$

Chu and Xu (2022) model the agent's decision to invest its labour on producing hunting-gathering or farming resources to maximise food production *x* given by (**9**):

$$x = h + f = \frac{l_H}{l_H N}^{\gamma}(Z_H)^{1-\gamma} + \varphi(l_F)^{\alpha}(Z^{1-\alpha}) = (l - l_F) \qquad \textbf{(9)}$$

A condition for a farming system is that most of the labour is destined to produce agricultural resources (**10**):

$$x = f = \varphi l^{\alpha}(\frac{Z}{N})^{1-\alpha} \qquad \textbf{(10)}$$

Thus, during the gradual transition from hunting-gathering to agriculture, the per capita output of food production is given by (**11**):

$$x = h + f = (l - l_F)\theta(\frac{Z_H}{l_H N})^{1-\gamma} + \varphi\rho^{1-\alpha}l \qquad \textbf{(11)}$$

Following this formula, the level of farming productivity increments as more labour is allocated to the production of this resources. According to this model, if the population fails to reach the agricultural threshold, it will remain as hunter and gatherers. In this case, Chu and Xu conclude that a high agricultural productivity and high level of labour supply would have been paramount for the Neolithic Revolution.

2.3. Why agropastoralism?

The empirical evidence defines the '*when'*, '*where',* and '*how'* communities started to manage and modify animal and plant breeding, adopted sedentarism and modified their risk management strategies to ensure their long-term survival. However, the '*why*' is practically invisible in the archaeological record as it involves the reasoning of past communities on how they perceived their world, how they interacted with it and what were they interests and goals. Multiple hypotheses have been suggested to explain this change and they can be divided into three principal categories: *environmentally driven resource pressure*, *demographically driven resource pressure,* and *internal pull factors.*

2.3.1. Environmentally Driven Resource Pressure

This hypothesis argues that the domestication process was a consequence of the climatic changes that took place during the Younger Dryas (c. 12,9 - 11,7 ka cal. BP), which caused colder and drier temperatures (Fawcett et al., 1997; Alley, 2000; Mangerud, 2021). In this reasoning, agriculture is understood as a strategy to overcome that severe weather conditions and ensure their survival. This hypothesis was developed by Childe in 1929, naming the 'Oasis hypothesis' (also known as the 'propinquity' or the 'desiccation' hypothesis) suggesting that during the PPNB there was a radical climatic deterioration that destabilised population lifestyles. To survive, humans and their future domesticated animals (they selected the most docile and suitable animals for being domesticated) concentrated together in well-watered locations such as oasis and river valleys. That interaction led ultimately to domestication and, finally, to agriculture. By learning how to cultivate and herd, they combined two systems of mixed farming, and people were able to live in established villages and reproduced rapidly. The invention of farming, therefore, allowed people to improve their lives since previously, during the Mesolithic, they were 'in extreme poverty'.

From this approach, Mesolithic and Neolithic people were completely differentiated populations. On the one hand, Mesolithic people were defined by their mode of subsistence: their principal characteristic was 'not being farmers' and, thus, they had to move around a lot, to live in small groups and to produce flints and bone tools as technological tools. On the other hand, there was the Neolithic 'culture' with domesticated plants and animals, sedentary, lived in the community and produced pottery, polished stone tools and symbolic objects, much more sophisticated artefacts. Archaeologists followed this typological dichotomy to establish chronologies of what was 'Mesolithic' and 'Neolithic'.

While Childe's hypothesis awoke interest to explore the origin of agriculture and to understanding this process, it was dismissed during the 1940s and 1950s when climatic studies proved a gradual climatic change (Godwin, 1948) and the archaeological record evidenced farming activities before the Younger Dryas during a period of good climatic conditions (Bowles & Choi, 2019). Yet, it has represented the starting point to develop more hypotheses about the origins of agriculture.

2.3.2. Demographically Driven Resource Pressure

In the 1960s, the conceptualisation of the domestication process adopted an alternative approach. The study of the origins of agriculture was revolutionised by the application of the archaeological science and the development of the so-called 'New Archaeology' (also known as Processual Archaeology). It represented the onset of the integration of archaeological and palaeoecological data and an increase in attention to environmental elements within the analyses of the archaeological record of early farmers. Thus, a renewed focus of study was to measure the productivity of farming as a critical factor that would have originated other changes. Researchers focused on defining the inputs and outputs of food production versus foraging to establish the equilibrium at carrying capacity. Feeding this new evolutionary archaeology, the formulation of OFT (MacArthur & Pianka, 1966) represented a turning point on the study of the transition from foraging to agropastoralism as it proposed that natural selection favours animals whose behavioural strategies maximize their net energy intake per unit time spent foraging (including searching, killing, processing, transporting). In this manner, this approach offered a way to formulate mathematically individuals' preferences over resources. That was the basis for the development of new theoretical approaches like demographic pressure hypothesis.

In 1968, Binford proposed the development of the Neolithic was due to a critical population growth which forced people to move into marginal areas and, consequently, diversify their subsistence to survive and that led to the first manipulation of cereals. This approach was constituted from the premise that there was a systematic relationship between humans and environment, in which culture represented the intervening variable to obtain the equilibrium (Binford, 1962: 218; Binford, 1972).

Within this line of research, Flannery (1969: 77) coined the term 'Broad-Spectrum Revolution' (BSR) to the hypothesis that argued that foragers had to diversify their diet (specialization on hoofed animals combined with small mammals, fish, turtles, waterfowl, snails, and other marginal resources) because of the imbalances between population and environmental carrying capacity. Flannery suggested that this broadening of subsistence resources could be explained using Binford's model of population growth and disequilibrium (Binford, 1968), where population growth forces people to move into marginal areas and to diversify their subsistence to maintain a living (Earle & Christienson, 1980: 38). The need of foragers to diversify their diet was also claimed by Smith (1975) with his 'overkill hypothesis' that proposed that the extinction of large herding mammals due to excessive hunting would have caused a specialisation of hunting for maximising its efficiency.

Following the same principle but from another perspective, Cohen (1977) supported this theory by suggesting that foragers probably exceeded their environmental carrying capacity, so they had to start storing food and that pushed them to experiment with plants and animals to maximize their food and that ultimately resulted in the development of agriculture. This 'experimentation process' would have taken place in a dynamic context of demographic context and varying plant and animal densities (caused by human overconsumption). He argued the BSR also represented the beginning of plant cultivation, and it was followed by increased specialisation focused on few domesticated animals and plants in correlation with population growth (Cohen, 1977). Consequently, the adoption of agriculture resulted in a net increase in the workload and a decrease in food diversity and sufficiently, and therefore an overall reduction in the quality of life, a situation that any rationally minded hunter-gatherer would not enter freely. With the adoption of a village-based life and domestication, there would have been a birth increase and some people had to evacuate to neighbouring regions, expanding agriculture on their way. From this view, farming originated a demographic expansion as it allows to produce food faster and more efficiently.

Nevertheless, there is no consistent evidence proving that farming is more productive than foraging strategies. It has been defined from modern agronomic studies and experimental archaeological studies, but it is difficult to quantify these values. Additionally, research in last years has demonstrated that unlike the traditional view that farming increased demography, it caused almost eight centuries of stationary or even declining population (Bocquet-Appel, 2002; Bocquet-Appel & Naji, 2006; Guerrero et al., 2008). In fact, the long-term demographic expansion was probably possible for the sedentarism, as shorter birth spacing was possible (Lambert, 2009; Bocquet-Appel, 2009).

2.3.3. Internal Pull Factors

Instead of focusing on external push models, like environmental or demographical factors, there are other authors that suggest internal pull models as the causes for the origin of domestication. They advocate for the inherent capacities and characteristics of humans as the factors that culminated in the emergence of early agropastoralism. The first author suggesting this approach was Braidwood and Howe, who argued that people lived thousands of years surrounded by the future domesticates so they acquired a deep knowledge of the environment, natural and faunal practices that led them to develop technologies to control them (Braidwood, 1960; Braidwood & Howe, 1960).

Another example is Hayden (1990), who put forward the competitive feasting hypothesis arguing that food was regarded as a source of social prestige and food production allowed to supply unique products with superior social status. Like so, it was considered as an endogenous social change, particularly the development of prestige economies the mechanism for change in these models is status-seeking individuals, who encouraged and controlled the growth of potential domesticates such as competitive feasting, alliance formation and extortion, then as primary sources of food. The PPNB would have generated differences in social status amongst Levantine communities and, to avoid an overly rigid hierarchical society, the neolithic colonizers escaped to a more egalitarian social system. According to this approach, domestication and agriculture would have emerged in resource-rich zones as they would have been the first to develop social inequalities and these elites would hold competitive feasts offering the 'first domesticated plants and animals' in form of prestige goods and delicacies. This theory does not require archaeological evidence for resource stress and malnutrition caused by population pressure or climate change, as the previous ones. In fact, it appears that early domestication unambiguously consisted of important food rather than delicacies (Smith, 1995). Nevertheless, the first foodstuffs produced were not delicacies and that makes this hypothesis not widely accepted.

In relation to internal pull hypothesis, a relevant proposal is Cauvin's psych-cultural model (Cauvin, 1994, 2000a, 2000b) suggesting that during the PPNA there was a raise of the mother-goddess deity that inspired the initial domestication, and it was during the PPNB when the cult to the bull deity gained importance, establishing a more natural predator-prey relationship. Cauvin identified as evidences the semi-subterranean circular houses of PPNA inspired to the feminine form and the rectangular shapes of PPNB with the straight lines of masculine body. In this line, Mithen (1996) also supported the view that the origin of agricultural can be explained as a fundamental change in the way the human mind conceived of nature. Prehistoric foragers presumably saw themselves as part of the cosmos, along with the animals they hunted and the plants they gathered. Once people became farmers, the cognitive world must shift profoundly from a sense of belonging to and being part of the wild to 'acculturating' it as it became something to control and appropriate rather than be part of. In the same way, Hodder (2001) stated ideology was the driver of subsistence change. One of the most viable theories is it allowed a rapid economic growth which led to food surplus that early farmers could provide for the members of the community that were not food-producers (i.e., craftspeople, chiefs).

Also emphasising the importance of control, Diamond developed in 1997 the biogeographic hypothesis arguing that societies that transited early into agriculture in prehistory achieved a head start over other societies in terms of social, political, and technological development. He suggested that the transition to agriculture occurred in Southwest Asia because of its superior biogeography provided suitable plants and animals to human populations for domestication. Once communities were fully sedentary and agriculturalists, civilised emerged with a codified language, large public monuments, religion, hierarchical power structures, and statehood. This hypothesis assumes a causal relationship between the development of agriculture and the rise of statehood: (a) early transition to agriculture led to the configuration of extractive institutions and, consequently, weak current economic performance and (b) late transition to agriculture led to the configuration of inclusive institutions and, consequently, strong current economic performance.

Diamond's hypothesis has served as a starting point for more recent studies of the emergence of agriculture approached from the economic literature such as Hibbs & Olsson, 2004; Olsson & Hibbs, 2005; Putterman, 2008; Putterman & Weil, 2010.

In the same way, economic literature has focused on the study of the importance of private property (institutional change) as essential condition for farming (technical change). The hypothesis of property rights was developed by North and Thomas (1977) arguing that technology gradually improved the level of productivity of foraging which caused an overutilisation of resources, causing a decline in foraging resources and increment of competition among the population. Dyson-Hudson and Smith (1978) also argued that territoriality was only worthwhile under conditions of high density and predictability, naming farming systems. On the other hand, they characterised people practising proto farming had property rights among their land utilising their resources more efficiently. Farmers ultimately increased the labour productivity of land, the labour force, producing an advantage in favour of farming.

Based on these premises, Bowles and Choi developed an agent-based model (Bowles & Choi, 2003, 2013, 2019) to explore the importance on property rights for early agropastoral communities. They designed a setting in which two agents -named Bourgois and Civic- from the same group randomly paired interact, and the game consists of how they distribute their resources according to their (a) subsistence strategy and (b) cultural model. (a) The Bourgais agent follows a 'farming-friendly property rights' strategy, in which never shares its own product and always try to steal foragers resources, whereas the Civic agent follows the 'sharing-enforcer' strategy, which goes against the Bourgais practices since it distributes the resources equally. (b) They are assigned different cultural models for both strategies. To define which strategy is more successful, the payoffs from farming and foraging are defined (**12**):

V_h : productivity of foraging

$$V_a = (r - \theta)z - z \quad \textbf{(12)}$$

Where:

V_a: productivity of farming

r: productivity of farmer's investment

θ: disadvantage of farming due to temperature volatility (for a detailed explanation see Bowles and Choi, 2013)

z: amount of farming investment

During the game, agents can change their subsistence strategies and migrate to more optimal locations. This model has been employed by other authors as well (e.g., Gallagher et al., 2015) to explore private property in the Neolithic. Following this, Bowles and Choi (2019) argue that farming would have represent an unlikely choice without possession-based private property, which probably existed among some of the people that first selected and controlled plants and animals. According to them, a would-be first farmer would be unmotivated to undertake the long-term production process and fixed investments that farming required, but the novel rights required to motivate farming could not be adopted singly (Bowles & Choi, 2019). Therefore, farming could have benefited first adopters because private possession was more readily established and defended for cultivated crops and domesticated animals than for the diffuse wild resources on which foragers relied, thus explaining how farming could have been introduced even without a productivity advantage.

From this approach, a specific topic in which researchers have focused has been on the potential egalitarian behaviour of early agropastoral communities. Egalitarian behaviour can be described as a type of political action that restricts activities and practices exclusionary power (Blanton, 1998; Feinmann et al., 1995; Dueppen, 2012). In prehistoric archaeology, some authors have described this behaviour for past communities when they 'deliberately affect community behaviour and social relations by emphasising shared identity and affinity' (Kuijt, 2002). This kind of behaviour has been identified in early agropastoral communities of southwestern Asia, when various types of settlements, structures and types of burials are identified (e.g., Finlayson, 2020; Morales & Rodriguez-Lara, 2020; Benz, 2019).

2.4. Across the Mediterranean

The earliest territory with evidence of human control on plant and animal populations outside of southwestern Asia is the island of Cyprus. During the PPNA, the first remains of a mixed economy including domesticated animals (e.g., small pigs, cats, and dogs) and plants (e.g., cereals) are found. However, it was during the PPNB that herding animals such as cattle, goats and sheep were introduced. The different stage of the introduction of animals is explained as changes in networks contacts between Cyprus and southwestern Asia, favouring some imports over others depending on the period. Not only resources migrated, but also genetic evidence has proved that people moved from southwestern Asia to Cyprus although there is a consensus that we cannot claim a 'migratory movement' (Lazaridis et al., 2022), in the sense of migration as movement of many individuals across generations. According to this, their presence in Cyprus had the aim of exploring and acquiring seafaring knowledge so the next generation would be able to migrate towards other territories (Peltenburg et al., 2000: 852).

Besides Cyprus, which represents an exception, the expansion process of early agropastoral communities from southwestern Asia until the Iberian Peninsula lasted about 2,5 ka years. The archaeological evidence indicates a two migration routes: one though the Balkans reaching central and western Europe through the Danube valley and the other one through the Mediterranean until the Iberian Peninsula. In this study we will focus on the Mediterranean route.

From southwestern Asia, communities expanded towards Anatolia, evidence of agropastoralism in central Anatolia date by 10,2 ka cal. BP (Baird et al., 2012; Stiner et al., 2014). Between 9,9-8,5 ka cal. BP, early agropastoral communities spread west of central Anatolia reaching the Aegean coast (Ozdogan, 2014; Weninger et al., 2014). The first Aegean islands being occupied were Youra, Naxos, Ikara, Kythnos and Crete (e.g., Strasser et al., 2010; Carter et al., 2014, 2016). Early habitants of these islands were semi-sedentary or sedentary and their diet was based on agropastoralism (especially on sheep, goat, cattle, pig, and crops), although foraging still played a crucial role (Reingruber et al., 2017; Perlès et al., 2013).

Southern Greece was also occupied during that period, c. 8,7-7,9 ka cal. BP, with more consistent evidence in 8,4 ka cal. BP, when activities inside caves decreased in favour of an expanding, open-air settlements near the coast, where communities practised a mixed-agropastoral diet (Weiberg et al., 2016). Settlements were generally located on well-watered plains and placed with good resources availability. At that time, the Eastern Mediterranean region was dominated by wetter conditions (Weiberg et al., 2016: 42; Karamitrou-Mentessidi et al., 2013) and that has been pointed out as the cause of a latter occupation of the Aegean in detriment of Cyprus.

The arrival of early agropastoral communities in the Aegean and southern Greece has traditionally been described as 'abrupt' and in form of a 'maritime colonisation', forced by the 8,2 ka phenomena consequences in southwestern Asia, but radiocarbon dates have demonstrated their arrival was prior to the cooling event. After reaching the Aegean, the Neolithic expansion ceased for c. 500 years and, begun again by the end of the 8,2 ka (De Vareilles et al., 2020), suggesting the environment was a determining variable for farming spread. Therefore, some scholars claim this event would have hindered the expansion process towards other territories until wetter climatic conditions occurred (Krauß et al., 2014; Weninger et al., 2006). Nevertheless, other researchers argue the climatic change was very gradual, spanning from 8,5 to 7 ka cal. BP so the cooling event would have had minor effect (Finné et al., 2019). In any way, it seems that the expansion process reassumed after the cooling event which has been linked with a potential population increase (Birch & Vander Linden, 2018; Silva & Vander Linden, 2017; Alexander, 2005).

The Italian southern region represents the earliest territory of the peninsula with evidence of agropastoralism, which was fully spread throughout the Italian territory by c. 7,7 ka cal. BP (Pessina & Tinè, 2008; Branch et al., 2014; Starnini et al., 2018). Some of the earliest sites were location in the Tavoliere plain of Apuli where around a thousand ditches settlements were built (ranging from 1 ha to more than 20 ha), such as Passo di Corvo or Tavoliere sites (Malone, 2003; Whitehouse, 2014; Pearce & Whitehouse, 2014). It seems that new settlement shared common characteristics: a preference for open-air settlements in elevations below 500 meters (Biagi, 2003). The population increase and farming practices caused deforestation, visible from around 7,5 ka cal. BP (Colombaroli et al., 2008, 2009; Stoddart et al., 2019).

From Salento peninsula, two expansion routes emerged: one towards the Eastern coast and northern Italy (Fugazzola Delpino et al., 1993; Grifoni Cremonesi, 1992), and the other one from eastern Sicily towards the Tyrrhenian Sea (Guilaine et al., 2016; Natali & Forgia, 2018; Pessina & Tiné, 2008; Boattini et al., 2013) until the Gulf the Lion, of the Genoa -c. 7,7-7,6 ka cal. BP- and the Iberian Peninsula - c. 7,7-7,5 ka cal. BP- (Bernabeu Aubán et al., 2003, 2009; Gabriele et al., 2019; Martínez-Grau et al., 2020; García-Martínez de Lagrán, 2018). In fact, the expansion process from Italy to France and Iberia had a fast rate since sites located in Liguria (e.g., Arene Candide), southern France (e.g., Pont-de-Roque Haute, Peiro Sagnado), eastern Iberia (e.g., Mas D'Is) have similar chronology (Manen et al., 2019; Guilaine et al., 2007). The arrival of the Neolithic in Iberia could have been via maritime coast from the Gulf of Lion or via terrestrial route from southern France through the Pyrenees. In any way, the expansion of farmers in the Peninsula was fast and followed the main riverbanks (e.g., Ebro valley) (Baldellou-Martínez, 2011). It has also been suggested another route, from northern Africa until southern Iberia via de strait of Gibraltar (Morales et al., 2013; Isern et al., 2014).

The agropastoral communities that expanded from Italy, France, and Iberia (**Figure 4**) has traditionally been grouped by the stylistic style of the pottery that they produced. In this way, in the beginning of that north-western expansion, it would have the 'Impressa Ware' (Guilaine & Manen, 2021) and the later period there would have been communities producing 'Cardial Ware' (Barnett, 2000). Nonetheless, some scholars have demonstrated the contemporaneity of these two styles of pottery (Bernabeu & Martí, 2014; Rojo-Guerra et al., 2012), which would put under question the division of these two styles. On the other hand, what it has been observed is an interregional variance of crop packages throughout the Mediterranean (De Vareilles et al., 2020; Bouby et al., 2020; Pérez-Jordá et al., 2017). Despite same crops were introduced in the different territories, there were regional preferences and tendencies. For example, hulled crops were preferred until 5,5 ka cal. BP approximately, when there was a preference towards naked cereals and a reintroduction of some pulses such as bitter vetch or chickpeas (that had been practically abandoned). Other foodstuffs, such as the maritime resources maintained their relevant role in Mediterranean populations through time and space (Salazar-García et al., 2016, 2018; Goude et al., 2020).

Figure 4. Map of the settlements mentioned in Chapter 2.4.

2.5. Modelling the Expansion Process

The study of how the expansion process took place, how was the arrival of early agropastoral groups in territories inhabited by local foragers and how agropastoral lifestyle was ultimately adopted by communities, have traditionally encountered several difficulties in the Mediterranean area. Climatic conditions and poor preservation have made it challenging to recover archaeological material since most of the structures and artefacts are made of perishable material and do not preserve as well as in central and northern Europe. Neolithic open-air settlements tend to be flat in the alluvial plains and difficult to identify (Berger et al., 2016:67) and most of known sites are in caves and rock shelters, misrepresenting part of the sites. Even with these difficulties, the Neolithic is better represented in the Mediterranean compared to the Mesolithic record. To explain the scarce Mesolithic evidence, some researchers have argued that they had a low demographic density (Shennan & Edinborough, 2007), or that they abandoned territories because of the 8,2 ka cooling event (Fernández López de Pablo & Gómez Puche, 2009; González-Sampériz et al., 2009).

To explain the expansion process, ideally, we would have a good knowledge of how local foragers lived when early farmers arrived but despite the major advances and findings in the last decades, we are still far from this point. However, in general terms, research has been able to characterise the general nature of the process. Whilst traditionally there were two opposite models to explain the expansion, the *Demic Diffusion Model* (DDM) – people moved into other territories and established agropastoralism-, and the *Cultural Diffusion Model* (CDM) – ideas were transported instead of people-, thanks to the archaeological and genetic evidence (e.g., Bramanti et al., 2009; Pinhasi & Cramon-Taubadel, 2009; Balaresque et al., 2010; Shennan, 2018; Hofmanová et al., 2016; Gamba et al., 2012), it is broadly accepted that the expansion was made first through DDM and cultural diffusion had a secondary role (Fort & Pareta, 2020; Cobo et al., 2019; Fort, 2022).

This evidence has been possible thanks to the first modelling attempt of the demic diffusion based on Fisher's equation, developed by Ammerman and Cavalli-Sforza (1984), known as the 'Wave of Advance' (**13**):

$$s = 2\sqrt{aD} \qquad (\mathbf{13})$$

Where s is the speed of the population front of farmers, a if the growth rate of the farmers (is a measure of reproductive success), D is the diffusion coefficient of farmers (measure of how far away they move per generation, from birth to death). D function is called the dispersal kernel

(Clark, 1998) and the values are measured using histograms published in ethnographic reports of modern industrialized and/or pre-industrialised farmers (Fort et al., 2007). Similarly, a is estimated from ethnographic data (Ammerman & Cavalli-Sforza, 1984:155; Fort & Méndez, 1999).

As a result, the Wave of Advance predicts a spread rate of about 1 km/year on average that varied regionally (Bocquet-Appel et al., 2012; Henderson et al., 2014; Fort, 2015; Porčić et al., 2020). For example, for the coastal route, a spread rate of 8,7 km/year was estimated, and it was argued using numerical simulations that such a fast rate implies very long 'jumps' (dispersal movements) of at least about 350km per generation (Bergin, 2016). Additionally, some researchers have modelled the impact of sea travelling in the expansion model (Zilhão, 1997, 2003; Isern et al., 2017), matching with the archaeological evidence when considering a maximum of 150 km/year with a minimum sea-travel range of 300 km per generation.

Based on the Wave of Advance, Fort (2012) modelled the role of cultural diffusion in the demic model (**14**):

$$CE = \frac{s - s_{demic}}{s} \cdot 100 \qquad \textbf{(14)}$$

Where *CE* is the percentage of cultural effect, s_{demic} is the front speed predicted by the purely demic model (no cultural diffusion model). The model concluded that the importance of cultural diffusion in the Neolithic spread was less than 21% (Fort, 2022), confirming prior studies (Isern et al., 2012, 2017). In 2021, Fort developed a model of front propagation through oblique transmission exploring horizontal cultural transmission (acculturation of individuals of the second population by members of the first one and of similar age). This model went beyond the vertical cultural transmission (interbreeding) and considered the possibility that adult individuals taught members of the next generation (younger forager individuals).

The fast peace of the expansion is explained with the *leap-frog* movements (developed by Fiedel & Anthony, 2003 and tested by Isern et al., 2017), arguing big jumps targeting ideal locations for practising agropastoralism (i.e., close to water sources, good soil productivity and low elevation). Most likely both communities mixed differently depending on the region. While it looks like that, they occupy similar ecosystems (Vidal-Cordasco & Nuevo-López, 2021), some regions witnessed a hiatus between the occupation of last Mesolithic groups and early agropastoralists (Berger & Guilaine, 2009), and others were only occupied by Neolithic groups (Brisset et al., 2018; Cubas et al., 2016; Fano et al., 2015).

In any way, with the current evidence, it is possible to extract general tendencies and patterns of the expansion process such as agropastoralism was established throughout the Mediterranean with the migration of people, represent a rapid process, Neolithic people mixed with local foragers, but cultural diffusion was not the principal diffusion via of adopting agropastoral practices in these locations. Despite this broad knowledge, it is clear the expansion process was not uniform and unilineal in all regions. Likely local variations were present, and the general rhythm of diffusion also probably varied from the Aegean islands to the Iberian Peninsula (Manen et al., 2019; Guilaine, 2001, 2013).

2.6. Book Chapter

2.6.1. Barceló, J.A. & **Palacios, O.** (2023). Computational simulation of prehistoric migrations. Western Mediterranean Early Neolithic case study. In V. Heyd & M. Ahola (Eds.), *Moving and Migrating in Prehistoric Europe*. London: Springer Routledge.

Computational simulation of Prehistoric Migrations. Western Mediterranean Early Neolithic case study[3]

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Abstract

In this paper we deal with the archaeological study of population movements, currently labeled as "migratory". We develop the case of Neolithic population movements, especially the case of the arrival of new populations to Northeastern Iberian Peninsula from 5800 BC onwards. Our paper discusses some theoretical and technical approaches, making emphasis on computer simulation and agent-based programming techniques. We have also developed a machine learning model quantifying the influence of the environment (topography, temperature, pluviometry or soil productivity) and community organization (type of settlement, number of inhabitants or type of food to consume) on small-scale farmer communities that practice migration as a risk-management strategy to ensure their long-term survival. Our results on the causes and expansive dynamics of migratory movements in Western Mediterranean during the expansion of farming communities are compared with The *Human Securities Model* – Food, Environmental, Personal, Health, Economic, Community, and Political Security, defined by the United Nations (UN) Development Program's *Human Development Report*

Keywords: agent-based models, computer simulation, human securities model, machine learning, migration, neolithic, northeastern iberian peninsula.

[3] This paper is dedicated to the memory of Florencia Del Castillo Bernal, PhD, who passed away unexpectedly in September 2022, and who worked with us tirelessly on this project.

Introduction

Migration can be defined as people residential *and* labor displacement, both at the individual and at the group –population- level. That is, a process in which individuals and/or groups of people move to live and die where they were not born. People migrate today to increase their chances of survival, in the same way as they migrated yesterday (de Haas *et al*., 2020). In a way, migration is what has made us humans, since our foundational migration when an African species displaced part of its population to new lands, and we have continued to displace ever since.

As an example of a prehistoric migratory movement with relevant consequences across history, we study here the adoption of farming economic and social systems in Western Mediterranean, 7500 years ago, as the probable consequence of the arrival of migrants from Eastern Mediterranean or even furthest into the Middle East. Although farming was "invented" in an independent way in different parts of the planet, in many places, agriculture and herding were "adopted" as an innovation carried out by a new population that introduced the technique and new plants and animals whose normal behavior could be modified as a result of human involvement (domestication). In Western Mediterranean such a new population, moving from Eastern Mediterranean since 8100 BC, introduced in what are now Italy, France and Spain, from ca. 6000 BC onwards, new cultivated plants (wheat), new animals (sheep) and new tools (pottery), beginning a period of coexistence and social interaction with local hunter-gatherer communities, who adopted some of these new cultural features and found their own way to change and adapt to the new situation (Robb, 2013; Oms *et al*., 2016; Capelli *et al.,* 2017; Guilaine, 2017; Bernabeu *et al.,* 2018; Gibaja *et al*., 2018; Lugliè, 2018; Shennan, 2018; Manén *et al*., 2019; Bouby *et al*., 2020; Juan-Cabanilles and Martí-Oliver, 2019; Martínez Grau *et al*., 2020; Olsson and Paik, 2020; Rowley-Conwy *et al.,* 2020). We can analyze this historical case as an example of a prehistoric migration. In this contribution, we make emphasis on a computational simulation framework to describe and understand the process.

Why a new population left their homeland and arrived to Western Mediterranean at that particular moment? We should look to what happened at the original departure land of these migrants. The two most obvious consequences of the social and economic transformation experimented by the adoption of agriculture and herding at their homeland are assumed to be: a) a logistic growth of population and b) a relative low degree of infant mortality, given the new food resources – cereal flour, pulses, milk and its derivatives, domesticated meat- that were added to the traditional hunted wild meat and gathered vegetables (Borrell et al. 2015, Dunne et al. 2019, Palmisano et al. 2021).

To test whether population growth and local carrying capacities could have been the main causal factors explaining the departure from homeland and the arrival to a new colonizable land, we should reconstruct the displacement of people at those times. But social agents are for the most "invisible" in the archaeological record. The only chance to study "migration" in archaeological terms implies that we associate a particular observable feature with a particular human population, and that such feature can be identified over a very large geographical area. We can trace migratory movements looking for genetic or "cultural" (stylistic) markers. The problem with haplotypes as population markers is that it is not simple to differentiate a single population with them (Mahalaxmi et al. 2022). The same can be said regarding stylistic features of some human made tools or symbols. Strontium Isotope bioarchaeological data can be used to answer the questions of short-term/short-distance mobility rates, or population turnover due to immigration, as it captures the residential mobility trajectories of individuals. By using aggregate isotopic evidence for individuals from the same cemetery we can obtain averages of distance travelled by this people along their life (Bentley, 2006; Scaffidi and Knudson, 2020).

Let us assume that we have properly defined such a particular population marker, and it has been identified in a sufficiently large territory so that the only way it may have arrived at this place is by people moving. In our case, we can refer to Impressed Ware and the Cardial decoration style (Oms *et al*., 2016; Capelli *et al.,* 2017, Bernabeu Aubán *et al*., 2017a-b; Binder *et al*., 2017; van Willigen, 2018) as "cultural" markers (**Figure 1**). Recent palaeogenetic analysis has allowed a tentative pairing of these stylistic features with a relatively well individualized population from the genetic point of view (Bentley *et al*., 2012; Fernández *et al*., 2014; Olalde *et al*., 2015; Hofmanová *et al*., 2016; Omrak *et al*., 2016; Isern *et al.,* 2017a; Silva and Van der Linden, 2017; Garcia-Martinez de Lagran *et al*., 2018; Frieman and Hofmann, 2019; Aoki, 2020; Goude *et al*., 2020; Rivollat 2020, Loosdrecht 2021).

Figure 1. Impressed ware with Cardial Decorration from the Cova dels Fems archaeological site (Ulldemolins. Catalonia, Spain) © Cova Dels Fems Archaeological Research Team.

Where did the people carrying out this cultural and/or genetic markers come from? In archaeology, the only way we have to fix the geographical origin of a migratory movement is by looking for the oldest chronological mark of a particular cultural feature. Using radiocarbon estimates we can estimate the temporal position on a calendar scale of an archaeological item signaling the presence of the genetic or cultural marker at a precise place. The site location in which the *oldest* remain has been identified would then be the most probable origin of the phenomenon. The reliability of such estimation depends on the quality and exhaustiveness of archaeological data: if a majority of archaeological observations diagnostic of the presence of the studied population at a precise location have not been properly dated, we cannot determine the *oldest* place where the population has been observed.

In Western Mediterranean, items like wheat seeds and domestic sheep bones have not been identified in the archaeological nor paleoecological record before 6000 BC. The *oldest* seeds with botanical features evidencing their domestic origin – the substantial action of humans on them – have been identified in some areas of the Middle East (Arbuckle and Hammer, 2019), where we also find their wild antecessors in the landscape, and there is well preserved evidence of intermediate prototypes between the original wild and their evolved domestic descendants (Ibáñez *et al*., 2018; Abbo and Gopher, 2020). This is then the homeland of the supposed migrants having arrived at the Western Mediterranean.

On the basis of a hypothetical origin of the migratory movement in the Near East, we have developed a machine learning model quantifying the influence of the environment (topography, temperature, pluviometry or soil productivity) and community organization (type of settlement, number of inhabitants or type of food to consume) on small-scale farmer communities that practice migration as a risk-management strategy to ensure their long-term survival. Then, we have programmed a computer simulation to recreate what may have happened at this hypothetical place of origin to understand the potential dynamics of the migration process.

Understanding the Start of the Migratory Phenomenon: A Preliminary Machine Learning Approach

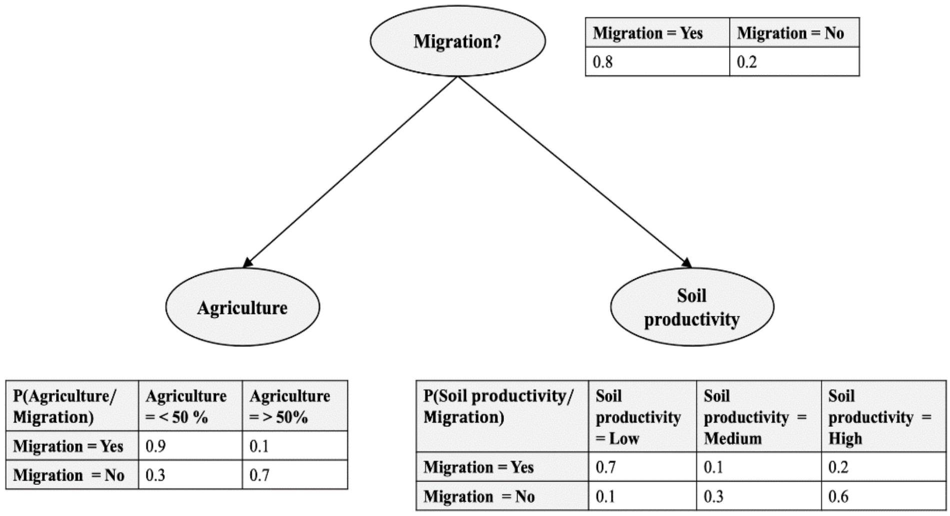
To explore to what extent migration is defined by the environmental characteristics, the type of food produced and consumed and the organization of the community, we have designed a machine learning model named ‘Agropastoral-management.v2’ (Palacios et *al.*, *forthcoming*). For building the dataset, we collected social, subsistence and environmental characteristics (**Table 1**) of 173 trans-historical and cross-cultural small-scale farming communities collected from two open-access repositories, D-PLACE (Kirby *et al.,* 2016) and eHRAF World Cultures (Human

Relations Area Files, 2022). We selected human groups of less than 1000 inhabitants that more than the 50% of their subsistence was based on agropastoralism (with other additional resources from fishing, gathering, and hunting). With these criteria, we aimed to select the most similar cases to early Neolithic communities but without establishing potential analogies between the ethnographical and the archaeological record. Instead, we used this kind of data to investigate the most probable behaviors that may have been practiced in the past and are difficult to identify using only the archaeological remains.

INDEPENDENT VARIABLES	**DEPENDENT VARIABLES**		
Environment	**Subsistence strategies**	**Social Organization**	**Social decisions**
Landscape	Agriculture	Community size	None
Distance to coast	Animal husbandry	Settlement types	Resource diversification
Elevation	Hunting	Community organization	Crop specialization
Slope	Gathering	Household organization	Foraging intensification
Annual mean temperature	Fishing		Storage
CV Annual temperature			Transhumance
Monthly mean Precipitation			**Temporal / Permanent migration**
CV Annual precipitation			Exchange in-/out-settlement
Monthly primary net soil productivity			Reciprocity
CV Primary net soil productivity			

Table 1. Summary of the variables considered in the Bayesian network model.

To achieve this aim, we built a machine learning model, a methodology that builds models from the dataset autonomously and it is automatically relearned from successive data updates (unlike classical statistical models which need to be redesigned from scratch). Despite the use of machine learning to explore past behaviors has incremented exponentially in the last decade (e.g., Ahedo *et al.,* 2019, 2021; Davis and Douglass, 2021; Monna *et al.*, 2020), it still represents a minority in comparison to other quantitative and qualitative methods. The reason for this is that some machine learning algorithms produce 'black box' models and, that is, they quantify the way that the variables are related but the mechanisms cannot be explained because they are not observable. To alleviate this deficiency, we have employed the Bayesian network algorithm in our study (Koller and Friedman, 2009). In Bayesian networks, the model is built from the data (as all machine learning algorithms) but the difference lies on the fact that its structure is designed from the conditional probabilities of each value given the prior variables. Consequently, it is a probabilistic graphical model that is 'white box' as its structure is visible and explanatory (**Figure 2**).



Migration = Yes	Migration = No
0.8	0.2

P(Agriculture/ Migration)	Agriculture = < 50 %	Agriculture = > 50%
Migration = Yes	0.9	0.1
Migration = No	0.3	0.7

P(Soil productivity/ Migration)	Soil productivity = Low	Soil productivity = Medium	Soil productivity = High
Migration = Yes	0.7	0.1	0.2
Migration = No	0.1	0.3	0.6

Figure 2. A toy example of a Bayesian network predicting the probability of migration considering the intensity in which agriculture is practiced and the soil productivity of the location.

Our results highlight the influence of *subsistence strategies* and *social organization* for defining the probability of migration. We have not identified a specific strategy that may be particularly related to a kind of migration, but it seems that in mixed economies based on agropastoralism, temporal and permanent migration represent a relevant management strategy to ensure the long-term survival. However, we were also able to observe some differences between permanent and temporal migration. Permanent migration is strongly related to the type of settlement in which the community lives in. That is, that the fact that people lived in a hamlet, a village, or in dispersed homesteads affected the probability that they would migrate permanently to another location. While permanent migration is definitive, temporal migration can be complemented with other social practices linked with movement of goods and foods such as exchange inside and outside the settlement or sharing foods for prestige in the community.

Interestingly, in our computational experiments migration appears to be not affected by environmental characteristics of site catchment areas around the settlement. People living in difficult environments were no more likely to migrate than those living in more productive environments. This suggests that farmers could compensate the resource availability, even in locations with low soil productivity or not especially suitable for practicing agropastoralism, with social decisions such as migration, but also by diversifying and exchanging their resources. This result does not imply that the environment had no effect at all; social organization changes correlated with changes in climatic conditions affecting productivity, and hence affecting the more probable type of settlement. Temporal migration is probabilistically related with the type of settlement.

Describing the expansive dynamics of Migratory Movements. An agent-based model approach

We have designed an agent-based simulation in which virtual agents are illustrated as computational representations of social agents extracting resources from the environment using finite amounts of labor force and a technology whose efficiency is an evolving parameter. In the simulation, probability of survival depends on the effect of five factors: the amount of resources at place, the capability of moving towards the place where resources exist in abundance, the quantity of available labor force, and the efficiency of technology used for resource acquisition and the efficiency used for storing acquired resources for the next time frame. Increasing the quantity of labor force and the efficiency of acquisition and storing technologies depend on social and political decisions, it is more probable to cooperate with people with similar culture than with people speaking a different language and without a common tradition.

In the first version of our computer model (NEOLSPREAD v. 0.4), there is a single kind of agent in the model: Farmers, but they also partially hunt and gather to obtain the subsistence they need. Each agent represents a group: a minimal unit of social reproduction (a “family” in colloquial terms). As such, they are computing units defined in terms of their *age, the number of members in the group, the acquired energy at current time, the technological efficiency at their disposal at current time, their culture* (a vector containing a series of independent features defining their language, moods, believes, etc. cf. Axelrod, 1997). Agents in the system have social and political ties with other agents (kinship, economic cooperation, political alliance, etc.), and they can also build power and dependence relations: lists of agents obeying orders by the agent, list of agents that may impose their orders on the present agent.

Such agents live in an evolving and changing environment, characterized by its topography, dominant vegetation type, water points, mineral resources, soil productivity of each place, and the erosion risk. Human agents extract energy from the environment and modify it when hunting-gathering and/or farming. Such modifications are determined by natural productivity, determined by fluctuations caused by a “climatic engine” governing temperature and pluviometry based on global paleoclimatic reconstructions. Environmental dynamics are also constrained by agents’ rational economic, social and political decisions and their indirect consequences, many of them probably unconscious and unexpected (soil nutrient depletion, ground cover loss), etc. The possibilities of advancements in technology to face such problems, like organized efforts to address soil depletion using rotation and cattle manure within large land-holding units will be considered in a future version of the program.

Agents reproduce according to biological and social/political constraints: population grows if agents acquire enough energy; population diminish in terms of mortality (age, violence and conflict, starvation) or by accident (labor hazard, biological risk, earthquakes, floods, droughts, etc.). Population grows logistically. After 17 simulated years, children within the agent become adults, and several new children born depending on the number of adults in reproductive age. Mortality is a non-linear function, so that all agents with an age higher than 60 die. This proportion diminishes with age, representing the rate of random accidental death. It increases in newborn children, so that 50% of children less than 3 years old die. Mortality is lower for children greater than 3 years old. Starvation is another source of mortality, and it depends on the differential between the number of agents at place, the total produced energy, and the possibilities of displacement for total or part of the population.

At each cycle –a simulated year- each agent PRODUCES energy through farming and CONSUME what it produces to SURVIVE. What an agent can produce in a year depends on the quantity of labor force within the group (proportional to the number of children and adults), natural soil productivity, temperature and raining conditions during this particular year, the efficiency of technology and the effects of diminishing marginal productivity from labor, soil nutrient depletion as a consequence of cultivation and ground cover loss as a consequence of herding. If the agent produces what it needs to consume, it SURVIVES. If what one group produces is not enough to support the whole group, that part of the group that exceeds the production capacity displaces to the nearest patch.

The decision to move and initiate the *migration* has been simulated according to these simple steps:

1. Calculate the current carrying capacity and the number of members of the current local group that cannot be supported –above survival threshold.
2. If the part of the human group that must be displaced has more than 4 adults, a new agent is initiated in another patch, and the previous agent loses that part of its original number of members. The new agent has no children in its initial stage.
3. If the part to be moved has less than 4 adults, no displacement takes place, and the mortality procedure (STARVATION) begins: the number of children and adults is reduced until arriving at survival threshold that fits available subsistence at place. When the number of members arrives to 0, the agent disappears.

The simulation is based on a low-resolution raster map of Eurasia from the Euphrates River to the Atlantic shores. The simulated area is around 5000 km from West to East, and 3500 km from

South to North. This area has been discretized in 1000x700 grid, so that 1 cell represents 25 km^2. Two different variables define each cell: topography (height above sea level), natural productivity (in terms of ecological yield or harvestable population growth of an ecosystem; cf. Schulp *et al.,* 2014). An additional binary variable distinguishes patches within the sea. More variables regarding environmental parameters will be added in new versions of the system. **Figure 3** shows preliminary of results of an initial historical scenario, where displaced new agents occupy a new patch at random, that is, without a rational decision "where to go next".

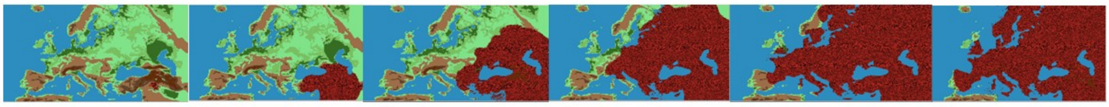


Figure 3. Running NEOLSPREAD 0.4. Programmed in Netlogo by D. Alexis [ETSE-UAB] implementing algorithms designed by J.A. Barceló, F. Del Castillo Bernal, F. Miquel Quesada, S. Pardo-Gordó, and X. Vilà.

With a sufficiently large number of precisely located and well dated prehistoric settlements, some form of reaction-diffusion mathematical model can be used to empirically test the pattern of mobility of migratory displacements in prehistory (Steele, 2009; Fort *et al.,* 2015; Silva and Steele, 2015). These are mathematical models expressing in formal ways the change in space and time of the intensity values of one or more variables. The *reaction* part of the model refers to local changes in which the variable(s) under study modify their intensity values, and the *diffusion* part, which describes how the new values spread out over a surface in space. Mathematically, reaction-diffusion systems take the form of semi-linear parabolic partial differential equations. It is the classical Kolmogorov-Petrovsky-Piskounov (KPP) equation (Kolmogorov *et al*., 1937), modified by Fisher (1937) to consider a logistic function for the growth or 'reaction' term. In this model, four parameters are used, two spatial dimensions (longitude, latitude), one temporal (calendar) estimation for each location, and an additional constant parameter representing the speed of the movement connecting the different points. The assumed constant population growth at origin – the point with the oldest temporal mark– is assumed to be the general cause of the movement. An additional parameter would be the maximum possible value of the population density at each location, that is, a limit of population growth assuming *saturation density* or *carrying capacity*.

Results from our agent-based model simulation do not fit the results of current reaction-diffusion models of the Neolithic (Rendine *et al*., 1986; Cohen, 1992; Fort and Méndez, 1999; Fort 2012, 2015; Fort *et al*., 2016; Isern *et al*., 2017a-b; Kabir *et al*., 2018; Aoki, 2020). The reason is that human movement is fast never continuous nor totally unconstrained (random). When moving, there are always factors that enhance the probability of going to a particular location, or factors that prevent to arrive to that particular place or advance in a particular direction. The travelled distance does not vary at random, but it is constrained by the size of displaced population, or the residential/storing technology that should be transported, among other factors. Any model of migratory process should implement algorithms for constrained movement and rational decisions "where to go next".

The patterns of movement in any environment should be generated primarily by properties of spatial form, such as visibility, accessibility, and integration in a network of differentiated spatial units, and secondary by the particular social and cognitive response to those spatial constraints: the intentions of individuals are also important in determining the modes in which people move in some direction and the time necessary to arrive to the intended location (Llobera, 2000; Griffiths, 2012; Flad, 2017). Sometimes, factors constraining the direction and speed of movement are out of control of the social agent, as in the case of terrain conditions. That means that we should modify expected random walks for optimal paths algorithms (Verhagen *et al.*, 2019; Solmaz and Turgut, 2019).
Obviously, there are also social factors constraining movement. The new algorithm we should explore will be based on the following "rational" decisions by social agents: when the group splits up, it moves to the *highest productivity* patch within a given neighborhood area. Such decision implies:

- If several patches have the same productivity, the one with the easiest access is chosen: agents are assumed spend the least quantity of energy on mobility
- If the patch is occupied by another agent, it can be occupied provided: a) soil productivity is high enough, b) the local agent has the "same culture" (cf. Barceló *et al.*, 2013), c) climatic conditions are good enough for high productivity at the current "year", d) the total aggregated labor force of the new agent exceeds the aggregated labor force of the agent occupying the patch, and has a surplus to be invested on war activities, the "local" agent is displaced to a neighbor patch with less resources, losing in the displacement part of its population.
- If the patch is occupied for a large enough group able to "defend" their territory, the second "best" patch is sought in the area explored.

It is assumed that the current agent has explored its vicinity, and it memorizes all suitable places within a known radius (*fluctuating baseline of human residential mobility*; cf. Scaffidi and Kundson, 2020). The extent of such radius depends on the efficiency of mobility technology – an external parameter that can be fixed with different values to simulate different scenarios, or alternatively, fixed using empirical estimates based on aggregated strontium isotopic data. In such list, where-to-go-next patches are ordered by accessibility.

All those modifications to the initial scenario imply that an additional type of social agent should be implemented: the *local* hunter-gatherer population that may enter into contact with the new incoming population and constrain in different ways the displacement of the new group of people. The problem when introducing a new breed of virtual agents is that the expansion of the "Neolithic package" is not only the consequence of displacement of a particular population, but on the possibility of the adoption of new features by the local population. Social agents may *change* by themselves, adopting partially new ideas or behaviors "invented" by others, but with no population substitution (Barceló *et al*., 2014). Therefore, two different hypotheses should be tested in the case of the adoption of farming economy at Western Mediterranean: whether the *motion* was of people (demic motion) or of ideas (cultural transmission). In both cases, the mathematics of the model are the same, but initial parameters of logistic growth, and diffusion rate are different (Fort, 2018; Fort *et al*., 2018). It is usually assumed that ideas travel faster than people, therefore, demic migratory movements can be distinguished from cultural transmission of ideas, in the sense that the wave advancement is faster in the second scenario than in the first.

There have been a lot of modifications and developments of the classical Kolmogorov-Fisher expansive dynamics model for taking into account these new assumptions and offer more detailed null-hypothesis terms for testing more advanced simulated scenarios (Fedotov *et al*., 2008; Pérez-Losada and Fort, 2010; Isern and Fort, 2010, 2012; Isern *et al*., 2012; Kandler *et al*., 2012; Cohen and Ackland, 2014; Brami and Zanotti, 2015; Chen and Tsai, 2020; Fort and Pareta, 2020; Fort, 2020; Tsai *et al*., 2020). In any case, we should also take into account what continues to happen in the original land of the displaced people. Considering that displaced agents were expelled from the area where they were born because of a combination of political, economic and environmental set of causes, and also by people rational expectations, it is important to know the continuity of those circumstances at the homeland to discover whether new waves of population will abandon the same land and will travel the same route in the same direction. A single arrival of a population group has not the same consequences as if diverse population waves enter new land recurrently.

Discussion

We have just analyzed a minor part of the migration process: people displacement. We should never forget that early farmers' migration was social: early farmers arriving to the Western Mediterranean were not just a homogenous and closed demic mass but it was enmeshed in relationships with people they left behind and with farmers and hunter-gatherers they found in their way (Robb, 2013). To consider the new social bonds that may have emerged among migrants and non-migrants all along the process, we should add to our computer simulation the particular kind of social interaction at each destination defining the emergence of new communities in Western Mediterranean. Mechanisms for social interaction were constrained by the *rational expectations* of newcomers and local population at the moment of arrival.

When leaving the area where they were born, early farming migrants *expected* to leave away: a) a somewhat degraded natural environment, an environment whose current carrying capacity – related to the technology at hand – could not feed ever growing populations, b) a social environment at risk affected by natural factors: illnesses, climatic extreme variations, c) a social environment affected by political factors, such as cultural diversity and margination, political domination, social and political exclusion, and d), some early farming-pastoral groups may have migrated not because things were necessarily bad where they were, but because they saw the opportunity to reduce the cost of production effort maintaining the same social system when they move to a neighbor land (Kelly, 2019). That is to say, we assume people departed their homeland in search for increased *security*. Obviously, it transcends the mere "look for food". The current model of *Human Securities* – Food, Environmental, Personal, Health, Economic, Community, and Political Security defined by the United Nations (UN) Development Program's *Human Development Report* (UNDP 1994), can be used to understand migrants expectations (**Table 2**).

Forms of Human Security	**UNDP definition.**	**Potential impacts due to migration**
Food Security	Physical and economic access to basic food	The arrival of migrants without their own land may create a population-resource imbalance that puts pressure on the area's carrying capacity, affecting both newcomers and prior inhabitants. Longer term effects may actually increase food production due to increased labor force.
Environmental Security	A sustainable physical environment capable of sustaining adequate subsistence regimes and protecting against natural disasters	The arrival of migrants may place pressure on non-food resources (water, timber, grass, arable land) by increasing the effects of erosion, soil degradation, and deforestation, and affecting both newcomers and prior inhabitants. Longer term effects may be ameliorated by an increased labor force available to construct protective public works.
Personal Security	Protection from physical violence, whether in the form of state-sponsored oppression, war, ethnic tension, crime, or abuse	The arrival of migrants may lead to increased violence, both at the individual (within the group) and between-group levels, depending on the relations between groups.
Health Security	Access to adequate nutrition, health care, and a safe environment, particularly water sources	The arrival of migrants may threaten the health level of both newcomers and inhabitants by bringing new illnesses or increasing their likelihood of spreading. Migrants may include people with various medical skills, but their ability to contribute will depend on whether they can become sufficiently established in the new community.
Economic Security	Assured basic income and employment	The arrival of a new population may place pressure on the social mechanisms both communities have used to organize labor and consumption. It may alter prior levels of inequality and affect access to the means of production and consumption (including property rights). The arrival of the new population may also introduce technology or other innovations, affecting both groups.
Community Security	Social group membership, integrity of cultural identity	The arrival of a new population may lead to changes in the cultural identity of both groups, by altering social norms, introducing beliefs, languages, and material culture, by increasing cultural distance, or by imposing different forms of segregation (at the spatial and cognitive level). Long-term effects may include cultural coalescence, bricolage, or hybridization.
Political Security	Possession of basic human rights, e.g. access to political system	The arrival of migrants may threaten the way both communities arrive at decisions imposed upon the collective. Migrants may no longer have access to government in the same way that they did prior to the migration. Such changes may also affect the progressive disappearance of traditional social ties within groups and the emergence of new social ties, both within and between groups.

Table 2. Human security dimensions and potential impacts of migration. Table organized and edited by the Coalition for Archaeological Synthesis Task group *Long-term effects of past migration on human* security (Altschul, J., Barceló, J.A., Beekmann, C., Kandel, A., Kiddey, R., Kienon, T., Kintigh, K., Ortman, S., Ragsdale, C.)

The United Nations' apparently "modern" concept of Human Security provides a set of organizational themes that cross-cut and incorporate multiple anthropological theories on migration. As MacFarlane and Khong (2006, p. 146) argue: "The [*Human Development Report*

1994] offered the first substantial definition of human security: 'Human security can be said to have two main aspects. It means, first, safety from such chronic threats as hunger, disease, and repression. And second, it means protection from sudden and hurtful disruptions in the pattern of daily life."

As a direct consequence of abandonment of the original land where difficulties were identified, and the assumed higher food accessibility in the new land, the displaced population having arrived to a new land assume higher levels of security in the health and personal dimensions, because stressful situations at their homeland have been avoided. There is a concomitant risk on community security, however, because increased distance from homeland reduce potential social interaction with relatives, and it menaces the original wide group continuity (culture). If the new area is already occupied by a population with a different economic base (mobile hunting-gathering), an increase in violence and the need of defense and protection can be expected. The new scenario breaks also the possible continuity of political ties that had dominated the original group, imposing some new social problems that should be solved with potentially new institutions and political decisions.

From the point of view of local hunter-gatherers, the arrival of a new population has completely different security expectations. They may expect to be menaced by newcomers. The degree of challenge that indigenous population may afford would depend on the human density of both local hunter-gatherers and new coming farmers. However, the probabilities of conflict will increase as soon as farming practices may affect negatively environmental stability: deforestation caused by crops, and the acquisition of building materials and firewood, shrub layer decrease caused by domestic animals and increased risk of soil erosion. It is also important to take into account that herbivores may eat planted crops, and farmers may design massive kills of animals constituting the main prey of hunter-gatherers. Also given that farmers also consume wild resources, natural carrying capacity of the new land can be at risk. The mobility and low settlement density of the economic base of hunter-gatherers may be an advantage, but only in case the expanding farmed landscape does not advance at a too fast pace. Although the main resource – wild animals – is also a mobile resource, the way hunter-gatherers are forced to displace do not necessarily follow the pattern of mobility of their usual preys, that can also be appreciated but newcomers, who have not entirely abandoned hunting and gathering. In some scenarios, it is imaginable that hunter-gatherers may evaluate positively some aspects of the new technology and economic behavior, however, as suggested by Robert L. Kelly (2019) we should take into account that most hunter-gatherers did not decided rationally to become farmers but they adopted some aspects of the farming system trying to keep alive their way of living.

In the new situation of potential conflict, division of labor may be expected to emerge, both at the local (within group) scale and at the global (between groups) scale. Some tasks related to the growing complexity of social interaction tasks need to be specialized, and probably evolve out of the direct subsistence work. Specialists (warrior, political, etc.) should be fed by the rest of the population. The risk of conflict diminishes the level of security in the personal and health dimensions, and the growing impact on environment may endanger even worst the situation. The effects on the security at the community and political dimensions seem obvious, conflict increases the internal ties group conscience (ethnic personality) and diminished reciprocity and cooperation between groups (cultural differentiation, ethnogenesis). New political relationships evolve to integrate the emerging unbalance between groups, the loss of autonomy when alliance between "equals" are needed, and the apparition of domination and coercion when some groups win the conflict over other groups.

Ethnogenesis, the particular way a human community builds is own conscience as a group is also a consequence of transformations, both within the group and between groups. What has traditionally been called "ethnic" differentiation is nothing more than a consequence of the diverse degrees of social interaction between different human groups, and an emerging pattern of social similarity/differences in social practices between groups. We assume that ethnogenesis and identity formation emerged among prehistoric hunter-gatherers as result of the contradiction between social inertia (knowledge inheritance) and cultural consensus (social similarity) built during social interaction –cooperation, labor exchange, conflict or domination between hunter-gatherers (indigenous) and different groups of farmers that may have arrived at different moments (earliest newcomers, secondary newcomers). *The lesser the intensity and frequency of inter-population relationships, the greater the differences in ways of speaking and other cultural features manifested by groups* (Barceló *et al*., 2015, 2019). If "culture" can be defined as the expected variance in a distribution of social values, goals and activities among synchronous human aggregates or populations, "ethnicity" can be approached as the degree of social inertia or resilience between different temporal states of the same aggregate or population, that is the ability of an aggregate of social agents to maintain a certain identity in the face of the changing pattern of relationships with other groups of the same population or even with different populations. Both "culture" and "ethnicity" are quantitative properties of human aggregates and not inherent features of individuals. Whereas "culture" expresses the degree of commonality in social activities between spatially differentiated but contemporary groups, "ethnicity" expresses the degree of similarity between non-contemporary human groups sharing the same area at different temporal intervals.

By using a common set of output variables, we can create an explanatory model of the possible consequences produced by migratory movements in prehistory. Up to now, archaeologists have lacked an integrated and comparative approach to analyze long-term impacts of migrations into a multi-temporal, multi-scalar model. The above seven dimensions of human securities – economic, food, health, environmental, personal, community and political – allow to integrate migratory movements in the past, with population movements in the present, and to understand the way human day-to-day experience may be affected by input variables such as size differentials between migrating and receiving populations, the duration of the migratory process, the nature of social and physical boundaries, and differences in the social and political complexity of migrating and receiving populations. We can use the entries in Table 1 to enhance the previous model of prehistoric migration to take into account social expectations. It implies to model new input parameters and output variables.

The calculation of the degree of environment, economic and food security for each agent does not need additional variables in our enhanced algorithm, just the relationship between population territorial density, their aggregated caloric needs and the aggregated value of natural and human produced resources. In any case, we need to monitor in the simulation how spatial features like soil natural productivity and erosion risk react to constant human impact.

To take into account personal security expectations we need to take into account the different possible forms of social interaction between groups. We should include the relationship between *locals* and *newcomers*, because the security expectation immediately after the arrival will be different. As Martínez Grau *et al*. (2020) has recently suggested, the pattern of contacts between these two generic populations in Western Mediterranean 7500 years ago is very complex, with some cases of colonization of a deserted area by the new population, some cases of direct head-to-head contact (possibly violent; cf. Meyer *et al*., 2018; Düring *et al.*, 201; Alt *et al*., 2020), and some cases of hunter-gatherer reaction to long distance social interaction (local adoption of new ideas). We should model the possibilities of peaceful contact (RECIPROCITY, COOPERATION), but also of violent interaction (DESTRUCTION, THEFT). Technology transfer travels between groups in proportion of the amount of cooperation and the establishment of kinship ties through exchange of reproductive agents between dissimilar groups (Barceló *et al*., 2015, 2019).

The perception of health security depends on the degree of violence between groups, but also on the expansion of new illness. Many of known diseases come from domesticated animals pathogens (Diamond, 1997), and therefore a new source of mortality (illness) should be implemented.

Community security implies the perception of the lack of variation of the group cultural identity. In some sense, what the social agent expects is to maximize in-group homogeneity and within-groups heterogeneity, in such a way that social agents tend to approach other social agents through a self-reinforcing mechanism of 'more interaction then more cultural similarity' (Axelrod, 1997). What defines the group (its "identity" at high scale) is usually a consequence of what members of such a group have learnt from their ancestors, and what they have learnt is a consequence of what those ancestors consciously decided to transmit to their descendants. Long-term communalities resulting from the repetition of interactions through generations is what constitutes the "ethnical" aspect of collective identity. On the other hand, we assume that communalities in belief and action do not exist forever because social similarity is in the process of continuous building, influenced by the very many aspects of social life. They are learned and shared across people. The challenge to this view is that instead of *assuming* that agents have common identity traits based on membership to an already existing "ethnic" group, agents ask themselves about the extent to which they are similar or different to others in the neighborhood (Romney *et al*., 1986, 1996; Romney 1999; Garro, 2000; Weller, 2007).

Beginning with Axelrod (1997), there has been a lot of interest to create computer models that may simulate the mechanism of cultural identity construction and transformation. Social agents expect that a sense of community would be maintained when social interaction restricts to the "culturally" homogenous group. However, there is always a random factor of change introducing minor transformations, apparently unseen during the life of a single individual that in the long run generates cultural groups that are so dissimilar from one another that their members cannot interact across group boundaries. R. Boyd, J. Heinrich, R, McElreath and P.J. Richerson (McElreath *et al*. 2003; Heinrich and Heinrich 2007) have proved that if people preferentially interact in with people who have the same culture as they do, and if they acquire their markers and coordination behaviors by imitating successful individuals, groups distinguished by both norm and marker differences may emerge and remain stable despite significant mixing between them. Under such rules, within a group the behavior which is initially most common will reach fixation, as individuals with the less common behavior are less likely to receive the payoff. The successful behavior will also develop a marker associated with it, as individuals sharing this marker will also be more likely to interact with each other and receive the higher payoff. These ethnically marked positions are examples of attractors within the model.

Domenico Parisi *et al*. (2003), working also on the lineage of Axelrod's assumptions, have simulated a process of expansion of a single human group in an empty territory and looking at what happens to this group's previous culture when during the expansion process both cultural assimilation between neighboring sub-groups and random internal changes in the culture of each subgroup took place. If within-group interaction preference is the mechanism by which global

convergence generates local diversity, then strengthening the tendency toward convergence might have the counterintuitive effect of allowing stable diversity to emerge.
Jamie Matthews (2008) has simulated the sudden arrival of a new "ethnic" group, and how it behaves with local populations. One might expect that in a culture with a very high rate of drift, new cultural regions may be absorbed very rapidly as common features may appear regularly by chance, facilitating interaction across boundaries. The results of this experiment suggest that despite such high levels of drift, distinct regions may persist for significant periods of time. In general though, it is possible to conclude that in relatively homogeneous cultures with low rates of cultural drift (as may be expected to be found in isolated, monoculture regions), any distinct cultures which do form are likely to persist for significant periods of time before being assimilated into the surrounding culture. These distinct cultures may appear through a number of possible mechanisms (including perhaps Axelrod's suggested local-interaction model), but an obvious example might be an invading or migrating group of people from a distant region with a very different culture. Finding aspects of culture in common with the invaders may be difficult, reducing the chances of further interaction and absorption. The second result suggests that even in a culture with a high rate of drift (such as a modern, fast-changing multicultural society) it may take a considerable amount of time for a new cultural group to integrate into its surroundings (Matthews 2008).

Simulating how distance and the progressive diminution of cooperation and interaction between increasingly divergent mobile groups, J.A. Barceló *et al*. (2013, 2014, 2015, 2019) have analyzed the emergence of ethnic fractionalization, cultural diversity and ethnogenesis. The authors have also suggested a set of Global Measures of Cultural Proximity and Social Inertia to measure the degree of cultural fractionalization and polarity based on observable cultural features as stylistic traits and differentiated behavior as evidenced in the archaeological record.

The last expectation of locals and newcomers, according to the United Nations (UN) Development Program's *Human Development Report* (UNDP 1994) is that referring to political security, that is, the degree of autonomy granted to individuals. That means, the degree all social agents may access public space, and in the same way, the degree of structural violence used by elites to restrict "freedom" of group affiliation and movement. Given that archaeologically we do not have any knowledge of the political structure of prehistoric hunter-gatherers and early farmers, we need to monitor the possible emergence of inequalities in terms of an architecture of power and social control, spatial hierarchy of sites, and evidence for territory control. In any case, beyond the "observability" of political structure, we need to implement in the simulation a causal model of *politics*. That is, how inequality and power relationships allow increasing economic, food and personal security. An interesting tentative in this direction is the formal theory of the emergence of inequality in apparently egalitarian social systems and subsistence economies suggested by Roemer (1982).

Conclusions

Social processes like population movements and economic change can be simulated computationally, and their temporal variation can be studied accordingly. The abundance and diversity of computer simulation of the process of early farming emergence, although different in scope, show the relevance and impact of this approach (Dreschler and Tiede, 2007; Barton et al., 2010; Rasteiro et al., 2012; Baum et al., 2016; Bentley and O'Brien, 2019; Saqualli et al. 2019, Fort and Pareta, 2020, Porčić et al. 2021, Cummings and Morris 2022, Pardo-Gordó and Bergin 2022), and also how the process ran in the Western Mediterranean (Bernabeu *et al.,* 2015, 2017, 2018; Bergin, 2016; Isern *et al*., 2014, 2017b; Pimenta *et al.,* 2017, Bergin 2021). It indicates that social dynamics can be explored algorithmically, and not that we have arrived to any kind of objective truth using computers.

Computer simulation allows the analysis of migratory processes, both in the present or from the most remote past as dynamic social systems whose evolution appears to be governed by their own "past", that is, what happened at the arrival at the new land "depends" on previous states of the process: the abandonment of the original land and the particular way displacement took place. In the same way, what happed after the arrival at the new land, also depends on what happened at the moment people entered the new land, and contacted –directly or indirectly – with local populations. In this sense, we should define human migrations as historical trajectories configured by a chain of dependency relationships, causal or not, between temporally ordered events. This means that human movement and its social, economic, cultural and political consequences cannot be understood as a disordered set of chaotic behaviors but that there should be transitional relationships that prescribe for each social event the possible 'next steps', and which states result from those transitions. Our aim is to discover these relationships of transition or change.

Our simulation is not limited to the Western Mediterranean Neolithic case study. If the archaeological proxies of human securities can be demonstrated, then it seems reasonable that the method could be extended to all types of migration, including contemporary ones. Importantly, the simulation will show not only when populations are likely to move, but under what conditions they will stay put (which, if keeping people in their homeland is a desired public goal, would be quite useful). This is crucial for our understanding of the migration processes because people not only moved, it was a complex process in which they also produced and consumed new resources, interacted with other cultures and communities, and shared and exchanged resources.

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Chapter 3

Early Agropastoral Systems in Iberia

3.1. Foraging Communities

The Mesolithic period dates in the Iberian Peninsula from c. 8,4-8 ka cal. BP until 7,7-7,5 ka cal. BP (Bernabeu Aubán et al., 2003, 2009; Gabriele et al., 2019; Martínez-Grau et al., 2020; 2018; Oms et al., 2017), when earliest evidence of agropastoralism is found. Our current knowledge of human groups living in the Iberian Peninsula during the Mesolithic is very disperse and incomplete. There are some regions better known as the Cantabrian coast while others, like the north-eastern, the southern or la Meseta, where it has not been until recently that some Mesolithic sites have been consistently dated and investigated (Arias, 2007). The fact that the number of Mesolithic sites in some regions is low does not imply that they were deserted, but due to taphonomy problems (e.g., soil acidity in the Atlantic coast) and lack of funding to investigate these areas (Rus et al., 2016).

This lack of knowledge about this period traditionally led to the belief that Mesolithic groups exclusively lived in rock shelters and caves, as they are locations which the scarce material evidence is better preserved and easier to identify. There are still some settlements with an unclear chronology and with an ongoing debate such as La Dehesilla, Los Alamos, Cueva de las Ventanas (Acosta, 1995; Riquelme, 2002), Cueva de la Dehesilla, Cueva del Parralejo, La Esperilla (López et al., 1996), or Cabezo de Lebrija (Caro et al., 1987). However, they do not represent the norm and, fortunately, in the last decades the number of known Mesolithic sites in Iberia has grown exponentially.

Although there were probably singular dynamics depending on the region, similar kind of sites are found throughout the territory. They lived in shelters (e.g., Bauma del Serrat del Pontcaves, Balma Margineda, Obagues de Ratera, Balma Guilanyà, Abrigo del Nacimiento, Abrigo de Valdecuevas, Bureco de Palo), caves (e.g., Cova Gran, Cova de Can Sadurní, Cova del Vidre, Coves del Fem, Cueva de Nerja, Buraca Grande, O Bocelo) and open-air (e.g., Sota Palou, Font del Ros, Orris de la Torbera de Perafita I, Bañugues, Oyambra, Prazo) settlements throughout the Iberian territory (Guilaine & Martzluff, 1985; Martínez-Moreno et al., 2009; Martzluff et al., 2012; Mora et al., 2011; Mas et al., 2018; Asquerino & Lopez, 1981; Sarrión, 1980; Aura Tortosa et al., 2009; Alcalde & Saña, 2017, 2008; Fullola et al., 2011; Bosch et al., 2022; Palomo et al., 2022; Rodrigues & Angelucci, 2004; Sanches, 1997). Some of them were seasonal settlements specialised on specific economic strategies, such as Montlleó site (Pyrenees) which was probably occupied during summer for hunting deer and wild goat (Mangado et al., 2010, 2011).

Another relevant type of settlement were shell middens where molluscs and other fish resources were exploited, found in Atlantic and Cantabrian coasts (Ramírez, 2007). However, in most sites fishing represented a minor activity (Salazar-García et al., 2018: 497, 2014) although its importance may be biased due to taphonomy (Revelles et al., 2018: 185). They had a broad-spectrum diet combining large and medium-sized mammals (e.g., wild goat, boar, red deer, roar deer, red fox, wildcat, Iberian lynx, wolf, rabbit) birds, fish, and molluscs (Aura et al., 2009).

3.2. Introduction of Agropastoral Practices

The Late Mesolithic, c. 8-7,5 ka cal. BP (Oms et al., 2017), is a chronological hiatus of c. 400-500 years in which late local foraging communities interacted with the earliest agropastoral groups that arrived at Iberia. At that time, the peninsula had a continental climate with gradually increasing temperatures (Catalán et al., 2012: 217) and defined by the mixture between the humid Mediterranean climate with Atlantic influences in the north and typical Mediterranean conditions in the south. Consequently, the area displayed a highly diversified climate which favoured the presence of a wide range of animal and plant species. First farmers settled in densely forested areas, with a predominance of deciduous broadleaf tree forests in the humid Mediterranean northeast and the Atlantic northern Iberia (Revelles, 2017: 440).

The paleoclimatic conditions of the north-eastern region has been more extensively investigated through pollen analysis and, only in this territory, a wide-ranging vegetal landscape is observed. In the Pre-Pyrenean area, broadleaf deciduous and riparian forests were present (Agustí & Roca, 1987; Buxó & Piqué, 2008; Piqué, 2000, 2002, 2005) while in the southern part of this region, evergreen *Quercus* formations dominated, including holm oak, pine forest and oak grove (Bosch & Santacana, 2009). In dry meadows, species such as ribwort plantain, docks, sorrels, mint, or burnet were found whereas in wet meadows lotus, swinecress or plantains predominated.

The arrival of agropastoral groups did not cause the disappearance of Mesolithic settlements or a radical change in the way that local communities lived. Some groups maintained their diet without introducing agropastoralism (e.g., shell midden sites, Cabeço de Pez) (Valente et al., 2014), while other included these other subsistence strategies adopting a mixed economy (e.g., Cabranosa, Padrão, Cueva Pena d'Água settlements).

Throughout Iberia, there were settlements with a continuity in occupation during the Neolithic period (**Figure 5**). In the northern region, Atxoste (Ruiz et al., 2012; Pérez-García et al., 2015), Cueva de Lumentxa (Aranzadi & Barandiarán, 1935; Arribas-Pastor et al., 2018), Cueva de Arenaza I, Pico Ramos, Cueva de El Mirón (Zapata, 2012), Pareko Landa (Quintana, 1996; Quintana & De Gopegui, 1997; Aguirre et al., 2000), El Forcón (Baldellou, 1987), Els Trocs (Rojo et al., 2016), Coro Trasito (Clemente-Conte et al., 2016), La Peña de las Forcas II (Utrilla & Mazo, 2014), Aizpea, Zatoya, Cova del Filador, Cova del Vidre, Coves del Fem (Bosch et al., 2022). In the south, we also have examples of open-air Mesolithic settlements that continued being occupied during the Neolithic period, such as Ambrosio (Jiménez Navarro, 1962; Suárez Márquez, 1981), La Carigüela (Pellicer Catalán, 1964; Toscano et al., 1997), Hoyo de la Mina, Nerja (Jordá Pardo, 1986; Acosta Martínez & Pellicer Catalán, 1997; Pellicer Catalán & Acosta Martínez, 1997), Bajondillo (Cortés Sánchez et al., 2007) or Cueva del Nacimiento.

Ex novo settlements of groups practising agropastoralism were also created. For example, in the Pyrenees and Pre-Pyrenees Cueva de Chaves (Utrilla Miranda & Laborda Lorente, 2018), Cova del Sardo, Abric de les Obagues de Ratera, Orris de la Torbera de Perafita I (Gassiot-Ballbè et al., 2021). In central Catalonia such as Cova del Filador, Cova del Vidre o Coves del Fem (Bosch et al., 2022; Oms et al., 2012, 2018; Mazzucco et al., 2016). In central Iberia, Neolithic sites of Cueva de La Vaquera (Estremera, 2003), La Lámpara, La Revilla and Los Cascajos (Zapata et al., 2004; Peña Chocarro et al., 2005). In the south, Cueva de El Toro, Cueva de los Mármoles, La Carigüela, Bats al Albuñol (Peña-Chocarro, 1999), Cabecicos Negros (Camalich & Martín, 1999), Zájara (Goñi Quintero et al., 2002), El Duende (Aguayo Hoyos et al., 1990), El Llano de las Canteras, Los Castillejos, La Molaina, Las Catorce Fanegas, Cerro de las Ánimas, Peñón de Salobreña, Cíavieja or Conchero de Cañada Honda (Barrera & Del Olmo, 1994; Reis et al., 2020).

They settled in different types of settlements such as hamlets, caves, rock-shelters and open-air with upraised structures are found. Due to taphonomy and anthropic processes, settlements located in rock-shelters and caves tend to be better preserved than open-air sites. In this latter case, buildings are usually recovered from stick holes (e.g., Balma d'Auferí or Barranc d'en Fabra sites), or storage pits (e.g., Guixeres de Vilobí, Mas d'en Boixos, La Serreta, la Vinya d'en Pau, Cinc Ponts). In few settlements has been possible to measure the size of occupation. In the north-eastern, settlements such as Plansallosa or La Draga had a surface of c. 1000-2000 m2, with ellipsoidal and rectangular huts (approximate 8-12 meters in length and 4-5 in width) (Mestres & Tarrús, 2009; Mestres, 1981), surrounded by fences to keep animals and cultivation fields. There were probably smaller occupations and size likely change through different events. For instance, in La Draga it is recorded an ongoing change and rebuilding of structures.

Caves and rock-shelters were also types of settlement commonly occupied. Despite they have traditionally been interpreted as secondary establishments related to main open-air settlements (Bosch, 1994), some of them were occupied permanently and had different uses. For example, Cova Colomera was used as a pen for sheep and goats but also used as settlements (Oms et al., 2015). Some were also used as base camps (for example, Cova del Frare, Cova del Toll, Cova de la Font Major) (Cabrià et al., 2014). These various settlement functions have been associated with transhumance and pastoral activities. Defined as long-distance herd mobility activities (Fernández-Giménez & Ritten, 2020), they are usually not defined in detail, and they are still not fully known how they were at that time (Antolín et al., 2018). Archaeological record provides evidence for the practice of at least short-distance vertical movements, from settlements located in the lowland to nearby pastures at higher altitudes (Gassiot et al., 2012b; García-Ruiz et al., 2020; Rojo Guerra et al., 2013, 2014; Tornero et al., 2016). Possible, rock shelters and caves could have played a relevant role as shepherd huts, enclosures, or shelters in case of unfavourable weather conditions (Palet et al., 2014). This is enforced by the evidence of pen deposits in caves (e.g., Cova Gran, Cova del Parco, Cova Colomera) (Oms et al., 2008; Angelucci et al., 2009).

Figure 5. Location of Mesolithic and Neolithic settlements mentioned in Chapter 4. 1. Abric de les Obagues de Ratera; 2. Abrigo de Valdecuevas; 3. Aizpea; 4. Ambrosio; 5. Arenaza; 6. Atxoste; 7. Bajondillo; 8. Balma d'Auferí; 9. Balma Guilanyà; 10. Balma Margineda; 11. Bañugues; 12. Barranc d'en Fabra; 13. Bats al Albuñol; 14. Bauma del Serrat del Pont; 15. Buraca Grande; 16. Bureco de Palo; 17. Cabecicos Negros; 18. Cabeço de Pez; 19. Cabezo de Lebrija; 20. Cabranosa; 21. Carrer de Reina Amàlia 31-33; 22. Caserna de Sant Pau; 23. Cerro de las Ánimas; 24. Cíavieja; 25. Cinc Ponts; 26. Conchero de Cañada Honda; 27. Coro Trasito; 28. Cova Colomera; 29. Cova de Can Sadurní; 30. Cova de la Font Major; 31. Cova del Filador; 32. Cova del Frare; 33. Cova del Parco; 34. Cova del Sardo; 35. Cova del Toll; 36. Cova del Vidre; 37. Cova Gran; 38. Coves del Fem; 39. Cueva de Chaves; 40. Cueva de El Mirón; 41. Cueva de El Toro; 42. Cueva de la Dehesilla; 43. Cueva de La Vaquera; 44. Cueva de las Ventanas; 45. Cueva de los Mármoles; 46. Cueva de Nerja; 47. Cueva del Nacimiento; 48. Cueva del Parralejo; 49. Cueva Pena d'Água; 50. El Carrer d'en Xammar; 51. El Cavet; 52. El Duende; 53. El Forcón; 54. El Llano de las Canteras; 55. Els Torcs; 56. Font del Ros; 57. Guixeres de Vilobí; 58. Herriko Barra; 59. Hoyo de la Mina; 60. La Carigüela; 61. La Dehesilla; 62. La Draga; 63. La Esperilla; 64. La Lámpara; 65. La Molaina; 66. La Peña de las Forcas II; 67. La Revilla; 68. La Vinya d'en Pau; 69. Las Catorce Fanegas; 70. Los Alamos; 71. Los Castillejos; 72. Mas d'en Boixos; 73. Montlleó; 74. O Bocelo; 75. Orris de la Torbera de Perafita I; 76. Oyambra; 77. Pareko Landa; 78. Peñón de Salobreña; 79. Pico Ramos; 80. Plansallosa; 81. Prazo; 82. Sota Palou; 83. Zájara; 84. Zatoya; 85. Cueva de Lumentxa; 86. Padrão; 87. Los Cascajos.

The seasonal circulation of herds was part of a small-scale intensive animal husbandry strategy livestock-oriented (focused on the consumption of ovicaprids). Similar management practices are observed in most of the Iberian territory: young animals were slaughtered for meat consumption and few adults were exploited intensively for secondary products (Rowley-Conwy, 2013) and transport activities related to farming (Saña, 2000). Intra-regional differences are observed concerning the animals preferred. For instance, in the north-eastern region preferences are observed: some sites consumed more bovids (e.g., Carrer de Reina Amàlia, 31-33) while others ovicaprine animals were favoured (e.g., Cova del Frare) (Saña et al., 2015; Saña & Navarrete, 2016).

This was combined with agricultural practices. It is likely that they worked the land through a small-scale intensive mixed farming system (Antolín et al., 2015; Antolín & Jacomet, 2015), as found in other Neolithic European contexts (e.g., Antolín et al., 2014; Pérez-Jordà & Peña-Chocarro, 2013; Bogaard & Jones, 2007; Bogaard, 2004). The principal cultivated crops were the so-known 'eight founder crops' but there was a broad diversity of plant resources: einkorn, emmer, durum wheat, common, hulled barley, free-threshing barley, pea, lentil, fava bean, bitter vetch, common vetch, grass pea, flax and poppy (Revelles, 2017; Antolín et al., 2015; Peña-Chocarro, 1999, 2007; Peña-Chocarro et al., 2005; Pérez-Jordà & Peña-Chocarro, 2013; Pérez-Jordà et al., 2011; Rovira, 2007; Zapata & Alday, 2007; Zapata et al., 2004). Preferences over plant species varied depending on the region. For instance, in the Meseta with colder environments, the consumption of einkorn and emmer was more stable rather than in the north-eastern area (Peña-Chocarro et al., 2018: 376). Besides the nutritional value of crops, their seeds were also employed as by-products for fermenting and producing dough that could be fired in the hearth.

Foraging activities were also relevant in their diet, but their importance varied depending on the region. For example, in the northern coast, settlements specialised on the consumption of wild resources such as Herriko Barra were located near other settlements with a diversified diet like Arenaza (Pérez Díaz & Peña-Chocarro, 2015), or in the south also wild animals were consumed with higher intensity than domestic animals (Saña, 2013). That does not imply that domestic resources were not relevant, but it was a mosaic-like system with different intensities and preferences, but with general patterns.

Hunting activities were generally reduced to a relative frequency of 30% at peninsular level (Tarifa-Mateo et al., 2023; Saña, 2013; Saña et al., 2020) although exceptions are observed in the northern and southern coast where wild animals represented between the 70 and 99% of faunal remains (Altuna, 1980; Mariezkurrena & Altuna, 1995; Saña, 2013). Generally, wild boar and deer were the only wild species that maintained their overall importance in diet during the early Neolithic (Saña et al., 2020; García-Martínez de Lagrán, 2018). Other species were consumed such as auroch, wild goat, Iberian wild goat, red fox, rabbit, or European pond turtle. Additionally, many different small mammals (e.g., fox, wildcat, or lynx) and birds (e.g., cormorant, woodcock, etc.) were also hunted. Another evidence of the continuity of hunting practices are the presence of projectiles, arches, and arrowheads in settlements. The skin of both domestic and wild animals was also be used to make recipients for cooking (additional to ceramic containers) with stones inside them, or the bones were used to make soups, other foodstuffs and even tools out of them.

Gathering continued playing a major role in the diet of agropastoral groups. Despite being underrepresented in the archaeological record when they were not roasted (Oms et al., 2018: 392; Antolín & Jacomet, 2015), in some sites like Coro Trasito, a wide range of different wild species have been recovered including hazelnut, acorn, rose, blackberry, red elderberry, grape, wild cherry, juniper, bog pine (Clemente-Conte et al., 2016). Leaves, aromatic and medicinal plants were also probably consumed (Antolín & Saña, 2022). Besides their nutritional value, most wild plants were used as fuel (i.e., acorns, pine, fungi), to manufacture tools (i.e., red elderberry, *taxus baccata*) (Piqué et al., 2015, 2020), and some for their medicinal value (Antolín & Jacomet, 2015: 23).

Like gathering, fishing is a type of subsistence that has rarely and discontinuously been detected due to problems of remaining preservation and recovery (Clemente-Conte et al., 2020). Recently, the question of whether fishing played a relevant role in the Neolithic package has been addressed and it seems that fish and shellfish consumption was reduced over this period (Salazar-García et al., 2017, 2018) and it only had a regional and local continuity (Mazzucco & Gibaja, 2018; Edo et al., 2022) but not throughout the peninsula (Blanco-Lapaz & Vergès, 2016). Malacological remains and shells were also used as raw materials to make tools and ornaments (Clemente-Conte & Orozco, 2012; Clemente-Conte, 2019).

For producing and processing food, various technologies were used. For processing plant resources were employed both lithic and wooden material. It is believed that lithic tools were used in non-woody plants and perhaps also to separate plant ears and roots from the rest of the plant (Gibaja, 2002; Clemente-Conte & Gibaja, 1998). Although these separated parts were not consumed, they were probably used to build structures, manufacture bakery, cordage, or clothes, as animal feeding or to temper ceramic containers. The most representative wooden tools were handles of sickles and adzes, digging sticks, combs, spatulas, ladles, bows, vessels, beaters, and projectiles (Revelles, 2017: 440; Bosch et al., 2006; Palomo et al., 2013). To reap, remove the animal's flesh and cut and manipulate animal skin it was preferred laminated lithic tools while to scrape wood or skin was more common to use stone chips (Palomo & Gibaja, 2001: 176). The tools used for conducting agricultural activities are the ones that have been more extensively studied using experimental archaeology and there are studies that explore the specific use of every tool. Conversely, the tools required for other activities are less investigated or they were the same than the ones used in farming. **Table 3** describes the principal tools for processing agropastoral resources.

Activity	Phase	Activities	Tools	Observations
Agriculture	Sown	Soil preparation	Digging sticks, beam, shovel	Demonstrates that cultivation was done individually or by few individuals
		Legume sowing	Digging sticks cone-edged	
		Wheat sowing	Digging sticks bevelled-edged	
		Sowing and transport	Bovine animals	
		Weeds removal	Digging sticks, beam, shovel	Demonstrates a limited prior soil preparation and cultivation close to forests and wetlands
	Reap	High-stalk removal	Reaper, sickle, blade	Probably stalks were removed by 12cm from the ground
		First winnow		For removing root remains
	Thresh	Wheat threshing	Bovine animals	It would indicate a significantly high production volume
	Winnow	Second winnow	Bovine animals	For removing micro remains
	Sieve	Microscopic separation	Sieve	No sieve has been recovered but the presence of extremely clean grains would indicate this process
	Wheat cleaning	Washing and drying	Hearth	
	Storage	Short-term	Baskets, ceramic containers	
		Long-term	Pits, aerial structures	
	Wheat processing	Grain roasting	Ceramic or skin containers and hearth	
		Flour	Grinding stones	
Animal husbandry	Cut flesh		Laminated tools	
	Remove skin		Stone chips	
Hunting and fishing			Bow, arrow, projectile point, spear, hook	
Food processing			Mixer, ladle, ceramic and textile container, spoon, spatula, stirrer	
Textile production			Comb, spindle-like needle, bone awl	
Building			Adze handle, wedge, shovel	

Table 3. Description of the tools for conducting the different socioeconomic activities present in early agropastoral settlements. This table has been developed based on (López-Bultó et al., 2020; Terradas et al., 2017; Piqué et al., 2015) studies.

Storage was essential to keep some seeds for the next crop season and some cereal surplus from the last production and use them for latter exchange, reciprocity relationships maintenance or bad harvests prevention. Recent studies claim that early farmers produced intentionally surpluses and generally, that would not be more than the 20% of the production (Pérez-Jordà et al., 2011; Oms et al., 2018: 392) as their capacity would have been around 500 litres, insufficient for maintaining a household (Prats et al., 2020). Additionally, meat and fish could have also been preserved by employing methods of fermentation, smoking or salt. Pits located near households were the most common structure to store foodstuff as seen in sites like Font del Ros, Caserna de Sant Pau, El Cavet or El Carrer d'en Xammar, for example. Once they had accomplished their use and were empty, they were refilled with garbage before their abandonment. While pits preserved in long-term, baskets made with perishable materials like cordage or ceramic containers were used for short-term storage. Aerial structures recovered in La Draga could have also been employed for long-term storage (Bosch et al., 2000: 75-78).

3.3. Model Overview

As summarised in Chapter 1, the SES approach supports the co-evolutionary relationship between the environment and social activities. To model past social activities and dynamics we need to consider the niche in which these actions took place and how societies modified their niche to meet their needs. Some of these actions are preserved in the record. For example, there is evidence of woodland cleaning, probably using fire (Kaal et al., 2008; Riera et al., 2004), for clearing out the territory to cultivate and graze (Mazzuco et al., 2015; Gassiot et al., 2012a; Gassiot et al., 2012b). For example, in La Draga site the earliest presence of occupation (c. 7,2 ka cal. BP) is related to a decrease of *Quercus* values (Revelles et al., 2016; Pérez-Obiol & Julià, 1994) and lakeshore peat deposits (Revelles et al., 2015; Revelles, 2017). Similarly, in the Pyrenees, the first evidence of cereal seeds is related to recurrent fires of woodland (Uría, 2013).

Another example of adaptative strategies of early agropastoral groups is found in the very fact that they located in a wide range of different niches. As seen in the previous section, communities lived in caves, rock shelters, open-air settlements located in lowlands, highlands, coastline, *inter alia*. They did not select specific places with the best conditions for practising agriculture and animal husbandry. With the current archaeological record, it is even questionable that given the possibility to select between a more optimal location and another less preferable for practising agropastoralism, they would have selected the most 'optimal' (defined by our modern standards: high soil net productivity, low slope, lowlands, etc.). If groups chose where to locate according to optimal criteria for exploiting resources, then we will find settlements where inhabitants consumed foraging resources and other settlement with only domesticated resources.

Early agropastoral groups had a mixed economy, consuming foraging resources in addition to plant and domestic animals. Also, their diet was not static, resources were consumed in different intensities depending on the settlement, the region, but also probably the period. However, this dynamism is difficult to identify in the archaeological record. As previously mentioned, some types of plants and animals were consumed with higher intensity, denoting a specialisation of some crops and intensification of foraging resources. The number of studies arguing the mobility of early agropastoral groups especially in mountain regions has also exponentially increased in the last years. Despite it is still do not know exactly the nature of mobility activities, it is evidenced that they moved into other locations. Movement of people, movement of resources, interactions among people inter- and intra-settlement are very difficult to identify in the archaeological record and they probably played a crucial role in the long-term survival of early agropastoral groups.

Many Mesolithic settlements continued being occupied by Neolithic groups, who introduced agropastoralism to these places. Therefore, it does not seem that the environment restricted subsistence strategies. That does not imply that the environment was not relevant for agropastoral communities. **To explore to which point environmental characteristics restrict socioeconomic strategies, this study aims to quantify the correlation among variables of social organisation** (type of settlement, number of inhabitants, relationship among population)**, socioeconomic strategies** (considering food consumed but also activities such as migration, transhumance, or exchange), **and landscape characteristics** (environmental and topographical characteristics of settlements).

To achieve this objective, we have employed data collected from ethnoarchaeological societies. Ethnoarchaeology has a long tradition in archaeology (David & Kramer, 2001; Ruibal, 2003; Kleindienst & Watson, 1956; Thomson, 1939; Trigger, 1989). Defined as a bridge between the archaeological record which is fragmented and static, and the dynamism and change that can be observed in ethnographic societies (Binford, 1983).

Ethnoarchaeology has often been used in the past to establish general laws of behaviour and validate archaeological hypotheses. This perspective is questionable. It is difficult to sustain the concept of 'general laws' as behaviour depends on many factors which can be particular of a specific context and, therefore, not applicable to other contexts. What we can do is to establish and measuring what behaviours are more 'probable' by considering all of them. Another aspect to consider is that the interpretation of the archaeological context is a result of the knowledge of the researchers, their beliefs, education, etc. It cannot be validated because we will never find a 'single reason' to explain the context. Different activities can produce the same result, and consequently, the maximum aspiration that we can have as archaeologists is to define which activity has the highest probability. When we work with ethnoarchaeology, we have the additional concern of analogy, we cannot aim to infer the knowledge obtained by investigating modern human groups to explain how people lived in the Neolithic. This is an inherent gap.

Ethnoarchaeology can be used to generate models and hypotheses to explore through the archaeological record, but not for validation. Similar to simulation models (Chapter 1), they allow us to explore aspects that are not observable in the archaeological record such as preferences, dynamics, social relationships. It can be used to suggest ideas but not to corroborate them. We have chosen this type of data because we wanted to investigate variables that they are almost unfeasible to have for prehistoric settlements, especially in Iberia, where research of this period is unequally distributed throughout the peninsula.

To explore the dataset, we have developed a Bayesian networks model to quantify the correlation among variables and to predict the most probable types of socioeconomic variables in specific socio-natural contexts.

3.4. Research Papers

The model is designed and applied in the following publication works (3.4.1. and 3.4.2.).

3.4.1. **Palacios, O.**, Barceló, J.A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. *Plos One*, *17*(10), e0276088. https://doi.org/10.1371/journal.pone.0276088

Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach

Ecology and social organisation in agropastoral societies through Bayesian network

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Abstract

The present contribution focuses on investigating the interaction of people and environment in small-scale farming societies. Our study is centred on the particular way settlement location constraints economic strategy when technology is limited, and social division of work is not fully developed. Our intention is to investigate prehistoric socioeconomic organisation when farming began in the Old World along the Levant shores of Iberian Peninsula, the Neolithic phenomenon. We approach this object extracting relevant information from a big set of ethnographic and ethnoarchaeological cases using Machine Learning methods. This paper explores the use of Bayesian networks as explanatory models of the independent variables –the environment- and dependent variables –social decisions-, and also as predictive models. The study highlights how subsistence strategies are modified by ecological and topographical variables of the settlement location and their relationship with social organisation. It also establishes the role of Bayesian networks as a suitable supervised Machine Learning methodology for investigating socio-ecological systems, introducing their use to build useful data-driven models to address relevant archaeological and anthropological questions.

Keywords: small-scale farming societies, Archaeology, Machine Learning, Bayesian networks, socio-ecological systems

Introduction

A socio-ecological system can be described as a structure defined by the interaction among social behaviours (e.g., subsistence strategies and social organisation) and ecological features of the location where social action took place (temperature, pluviometry, topography, soil features, etc.) [1]. This approach has been implemented in Archaeology and Anthropology among other Social Sciences to explore questions concerning how modern and ancient societies –even prehistoric- lived in the past and in the present and managed their environmental resources. Socio-Ecological System theory can be considered as a response to the limitations of traditional research approaches that addressed social modelling from reductionist assumptions [2]. From this perspective, past communities are not investigated in isolation anymore but considering the environmental and ecological characteristics that surrounded them and ultimately resulted from their interaction. Thus, the role of human agency for modifying and transforming the environment is recognised like the importance of the landscape to define human activities.

The debate concerning the relationship and interaction of early agropastoral communities with the environment has a long trajectory in archaeology (some examples include [3–6]). To address this topic, Niche Construction Theory has gained relevance in the last decades to study the plant and animal domestication process [7–11]. In this line, Smith argued in 2011 that early Neolithic communities were small-scale farming communities shared a similar behaviour: most of them had well-defined resource catchment/s area/s; they knew their ecosystem well and they constantly adapted to their own caused environmental modification [7]. That would have resulted in an increase in the probability of survival at those. However, probably not all the intervening factors (i.e., resource availability, prior knowledge, size of catchment area) had the same impact when early farming communities decided of what foodstuff was the best for their current situation. In fact, it was probably different for different communities, as additional particular variables may have been relevant given local conditions and circumstances.

Therefore, past communities constructed their niche by socially modifying their environmental conditions. There are numerous examples of prehistoric activities modifying the landscape with water [12] or fire to practice slash-and-burn agricultural method [13,14] or vegetation clearance for procuring pastures nearby [15]. These behaviours and cultural processes [16], not only modified the genetics of the species found in the niches (a clear example of that is the animals and plants genetic change with domestication), but also the way people lived, their households, their types of settlements, their relationship, etc. It was a reciprocal evolutionary process.

In this paper, we are interested in studying how prehistoric small-scale food producers [7] took social and economic decisions –where to settle- from their own observation of climatic and ecological features around them, the influence of the environment on their survival expectations and their knowledge of the possible consequences of their activity on that environment. We will focus our study on the maintenance of agropastoralism lifestyle of small-scale farming communities rather than investigating the origins of agriculture in itself. Our research should be considered as a new argument within the current trend of studies towards how early agropastoral economies were configured [17–19]. Beyond exploring a particular historical case, Old World Neolithic, for instance, we are interested in global dynamics, that could be of interest to understand different settlement patterns in different parts of the world in different chronologies. We would like to identify if there was some form of regularity or communality in potential socioeconomic behaviours of small-scale agropastoral communities that could be more likely to be present in some landscapes rather than in others. The goal is then to contribute to the understanding of eco-evolutionary relationship between the environment and people in the Past and in the Present, when industrialisation and market relationships are absent. To achieve this objective, we are asking two fundamental research questions:

Q1) Do ecological features of settlement location and/or social organisation constrained the type and intensity of subsistence strategies?

Q2) Do ecological features of settlement location and/or the type and intensity of subsistence strategies constrained social organisation?

Our research makes emphasis on the importance of the landscape to understand economic dynamics in communities with simple social organisation and low efficient technologies. However, we understand that the impact of topographical, ecological and climatic factors imply the study of multiple statistically causal (direct) and non-causal (indirect) links between the landscape -independent variables- and the human group -dependent variables- [20,21]. We have based our investigation on standard factors, already present in prior theories about small-scale farming communities through history (S1 Table). Among the landscape factors retained for analysis, we can mention elevation, slope, temperature variation, precipitation variation, natural soil productivity depending on soil composition, etc. Social decisions can be grouped into three main topics: 1) the strategy adopted to acquire subsistence (agriculture, animal husbandry, hunting, gathering, fishing); 2) features of the social organisation (community size, kind of settlement, local group organisation, household organisation) and 3) social decisions that can be adopted when survival is at risk (for example, in times of food scarcity) (**Table 1**). For instance, sometimes a human community can decide an economic strategy towards crop specialisation to compensate for diminishing marginal returns [22,23], or, alternatively, it can decide a diversification strategy for the same reason [24,25]. Exchange in goods and/or food can increase subsistence acquisition [26]; people displacement –migration- can be decided to better share existing resources [22,27,28], etc.

INDEPENDENT VARIABLES	DEPENDENT VARIABLES		
Ecology	**Subsistence strategies**	**Social Organisation**	**Social decisions**
Landscape Distance to coast Elevation Slope Annual mean temperature CV Annual temperature Monthly mean Precipitation CV Annual precipitation Monthly primary net soil productivity CV Primary net soil productivity	Agriculture Animal husbandry Hunting Gathering Fishing	Community size Settlement types Community organisation Household organisation	None Resource diversification Crop specialisation Foraging intensification Storage Transhumance Temporal / Permanent migration Exchange in-/out-settlement Reciprocity for prestige

Table 1. Summary of relevant variables to consider for modelling socio-ecological systems.

In this paper, we show how we can define hypothetically probabilistic relationships between landscape factors and different social decisional. That is to say, we analyse in which way the high elevation of a settlement area may constraint the adoption of resource diversification or crop specialisation; whether the role of annual precipitation of the region to be settled has any effect on the size for the human group that finally settled there.

The amount of influence and effect a variable has on any other can be expressed in probabilistic terms. We are looking for regularities expressed probabilistically to be able to predict and explain ethnological/archaeological observations. For instance, imagine we have documented a Neolithic settlement not far from a source of water, on the plain, in a region of low temperature annual variation (estimated from a paleo temperature record), and where grassland was the dominant vegetation. Built on that observation, we would like to predict that this community practised at that time an agriculture based on resource diversification without crop specialisation and a high level of external exchange. To formulate those predictions, we need to know the probability with which values of different variables may appear together. A usual source of error in this kind of studies lies on the assumption that input variables –climatic and ecological features of settlement location- are independent among them, and that all of them have a similar impact determining the output –the social decision. On the contrary, features like water, insolation, temperature, natural soil productivity, etc. are interrelated in a complex and non-linear way with feedback across variables defining the social behaviour [29].

The necessary probabilistic thresholds can be defined in terms of inductive regularities extracted from an exhaustive data set of well-known and described cross-cultural case studies [30–35], provided the database is big enough and it resumes the original social and historical variability. The application of trans-historic and cross-cultural data is particularly employed to evaluate hypotheses about Prehistory since the validation of social hypotheses about the past is often challenging [36,37]. Generalising from a rationally built set of particular cases is the most usual way to interpret human behaviour [38,39]. By learning what is common in living societies, we can mitigate the lack of this type of knowledge in the archaeological record.

The validity of ethnographic analogy has been strongly debated [40–42] because it employs the information of modern societies to interpret a possibly imagined past. Despite its inherent subjectivity, this kind of inverse reasoning approach can aid our interpretation of the archaeological record by providing information about what sort of behaviours could have been practised in the past. To measure the most probable behaviours, we need to collect the higher number of cases as possible to extract meaningful regularities to consider all the potential underlying variations of social decisions. This issue has been identified by many authors, and it constitutes the basis for modern ethnoarchaeological studies [21,43–45] which, again, does not attempt to draw direct analogies from the present to the past, but explore possible behaviours that may have been practiced in the past. In our case, to explore the probable communalities in small-scale communities, similar to those that may have existed in Prehistory, we have limited the learning data set to farming communities settled in not heavily transformed landscapes, practicing a mixed farming economy with low-efficiency technology and small quantities of human work [17,46–48]. This is the classical assumption of Prehistoric Neolithic Economies [3,49–51].

Among the many possible statistical and computational methods to compute similarity relationships and communalities among particular ethnographic cases, we have decided to use Machine Learning methods since they allow building models based on empirical data without prior assumptions. The resulting model is objective and captures the relationships between the variables in the collected data, without external intervention. Since the model is built from the dataset autonomously, it will be automatically relearned from successive data updates (whence the terminology "machine learning"). In this, it differs from a classical statistical model, which only captures the information of the moment and if new data is added to the dataset, the model is not automatically updated accordingly, but rather must be redesigned from scratch.

Many different Machine Learning methods have been employed to build socio-ecological systems, centred on understanding how people managed their environment [18,19,33,52]. Notwithstanding, the number of archaeological studies that use the Machine Learning methodology is still a minority compared to those that use other quantitative and/or qualitative methods. An additional problem is that many times the resulting model is just a "black box", suitable for some predictive tasks, but without explanatory capabilities, since the way the input is related to the output is not visible to the user.

To alleviate this deficiency, in this paper, we propose the use of *Bayesian networks* (BNs), which are a kind of supervised algorithm [53]. This method has only been previously applied in other research studies for designing a conceptual model [54,55] but not as the machine learning method that it really is (at least that the authors are aware of). Other studies that have explored past socio-ecological systems from the machine learning approach have employed other algorithms, such as logistic regression [56], deep learning [57], support vector machine [19], random forest [58] or combined some of these algorithms [18,59].

The remainder of the paper is structured as follows: the Materials and Methods section deals with the data and the method employed in the study, specifying the data collection process and the model building and implementation. In the Results section, the results obtained are presented and discussed in the Discussion section. Finally, the article summarises the most relevant insights of the study in the Conclusions section.

Materials and Methods

Data collection, cleaning, and pre-processing

To predict among the different possible ways small-scale human groups may have decided where to settle, we have investigated a trans-historical and cross-cultural dataset including 173 case studies collected from two open access repositories: D-PLACE [60] and The Human Relations Area Files (eHRAF) [61] (S2 Dataset). We have selected in both repositories cases for which detailed information for our list of variables existed and could be checked in the literature. Most data come from D-PLACE in first instance, and the Human Relations Area Files were consulted to check the information by reviewing the monographs of each community (S3 Dataset). Cases were deleted in case of inconsistency between these two repositories. Ethnographical cases were selected according to two criteria: *small-scale* and *farming* societies. That means, human groups –settlements- of less than 1000 inhabitants, and societies acquiring more than 50% of their subsistence from farming strategy: agricultural, and animal husbandry, with other additional resources from fishing, foraging, and hunting. In so doing, we have tried to minimise analogical bias by focusing our research on the most similar cases to the assumed target: Early Neolithic small settlements, where farming has been empirically established –domesticated plants and animals-, although there is additional archaeological evidence of alternative economic strategies. The resulting data set may be considered relatively small. It is however very coherent, and the underlying variation is meaningful and clearly related with the different ways these kind of societies exploited their hinterland. We have privileged the quality and reliability of the sample rather than the number and exhaustivity, provided social variation is not affected by the selection process.

Values for a total of 30 variables have been carefully recorded for each ethnographic case, based on the preliminary selection of independent and dependent variables (summarised in **Table 2**, see S4 Table for more detailed information). The quality of the detailed information in original sources is inconstant, and therefore we have standardised descriptions. Because usual Bayesian Networks link categorical variables, we have discretised quantitative values into uniform bins.

Information	**Variable**	**Values after discretisation**	**Variability range before discretization**
Environmental characteristics	Landscape	*Forest*	Tropical & Subtropical Dry Broadleaf Forests; Tropical & Subtropical Moist Broadleaf Forests; Tropical & Subtropical Coniferous Forests; Temperate Broadleaf & Mixed Forests; Temperate Conifer Forests; Boreal Forests/Taiga; Mediterranean Forests, Woodlands & Scrub
		Grassland	Tropical & Subtropical Grasslands; Temperate Grasslands; Flooded Grasslands & Savannas; Montane Grasslands & Shrublands
		Aquatic	Ice; Inland water
		Tundra	
		Desert	Savannas & Shrublands; Deserts & Xeric Shrublands
	Distance to coast (km)	*short distance*	< 10
		medium distance	10 - 50
		long distance	>50
	Elevation (m)	*low*	< 300
		medium	300 - 1000
		high	>1000
	Slope (º)	*low*	< 0.75
		medium	0.75 – 2.5
		high	>2.5
	Annual mean temperature (ºC/month)	*low*	< 5
		medium	5 - 20
		high	> 20
	Coefficient of variation temperature (ºC/month)	*low*	< 0.05
		medium	0.05 – 0.15
		high	> 0.15
	Monthly mean precipitation (ml/m2/month)	*low*	<95000
		medium	95000 - 130000
		high	>130000
	Coefficient of variation precipitation (ml/m2/month)	*low*	<0.06
		medium	0.06-0.08
		high	>0.08
		low	< 1

	Monthly mean net primary production (gC/m2/month)	*medium*	1 - 3
		high	>3
	Coefficient of variation net primary production (gC/m2/month)	*low*	<0.03
		medium	0.03-0.05
		high	>0.05
Subsistence strategies	Hunting (%)	*None*	0-5
		<25	6-15; 16-25
		>=25	26-35; 36-45; 46-55; 56-65; 66-75; 76-85; 86-100
	Gathering (%)	*None*	0-5
		<25	6-15; 16-25
		>=25	26-35; 36-45; 46-55; 56-65; 66-75; 76-85; 86-100
	Animal husbandry (%)	*None*	0-5
		<25	6-15; 16-25
		>=25	26-35; 36-45; 46-55; 56-65; 66-75; 76-85; 86-100
	Fishing (%)	*None*	0-5
		<25	6-15; 16-25
		>=25	26-35; 36-45; 46-55; 56-65; 66-75; 76-85; 86-100
	Agriculture (%)	*None*	0-5
		<55	6-15; 16-25; 26-35; 36-45; 46-55
		>=55	56-65; 66-75; 76-85; 86-100
Social organisation	Community size	*<200*	<50; 50-99; 100-199
		>=200	200-399; >400
	Settlement types	*Camp*	
		Homesteads	
		Hamlet	
		Village	
	Community organisation	*NA*	
		Clan communities	
		No exogamous clans	
	Household organisation	*Small extended*	
		Large Extended	
		Nuclear	
Social decisions	None	*Yes/No*	
	Resource diversification	*Yes/No*	
	Crop specialisation	*Yes/No*	
	Foraging resources intensification	*Yes/No*	
	Storage	*Yes/No*	
	Transhumance	*Yes/No*	
	Temporal migration	*Yes/No*	
	Permanent migration	*Yes/No*	

Exchange out-settlement	*Yes/No*
Exchange in-settlement	*Yes/No*
Reciprocity	*Yes/No*

Table 2. Qualitative variables and their categorical values investigated in this research. It contains the 30 variables and their values. Ecological characteristics of settlement location and its catchment area are defined in nominal scales using integrative categories.

In Machine Learning, training sets are usually huge, often in the category of Big Data. Nothing similar exists in the social domain, where the number of individual cases to be considered for induction and generalisation is by definition reduced. The advantage is coherence of the data set and the possibilities of reducing extrinsic variation. It implies, however, the need of grouping attributes to avoid the risk of over-particularisation.

The way we have integrated some classical environmental characteristics into global categories may seem unclassical, different from what has been applied in other studies. For instance, the category "Forest" in the qualitative variable "Landscape" integrates in the same category environmental settings such as tropical and subtropical dry broadleaf forests, boreal and taiga forest. Nevertheless, differentiating among types of "Forests" is still possible in our model given other variables in the dataset refer to climatic aspects like temperature and precipitation, both intensity and annual variation. Obviously, when grouping apparently different values into global categories we may lose information that could be relevant for characterising the individual characteristics of local ecological niches. It should be taken into account that we are interested in maximising global processes well beyond the local specificities. Given that we have restricted the number of cases for the reinforcement of data reliability, we have been also obliged to reduce the impact of individual details, that make reference to very local aspects. In so doing, we allow the calculation of potential *accurate* predictions, although we lose something in their *precision*. That is, we increase the possibility of finding global processes that may have acted in different contexts and historical scenarios, although such global processes may have had some local differences. Both accuracy and precision reflect how close a prediction is to an actual observation, but accuracy reflects how close a predicted value is to a known or observed value, while precision reflects how reproducible predictions are, even if they are far from the observed value at some particular circumstance.

This approach is necessary for any type of generalisation model. It applies in particular to Bayesian networks, for whose construction we have to estimate from the dataset the probability distribution of each variable conditioned to the possible values of its parents. Therefore, the more different categories the variables have, the more parameters we will have to estimate, for which we would need a dataset with many more cases than the one that we currently have.

Grouping categories and discretizing variables that were quantitative in origin has been carried out using the R software [62]: the function **discretize** of the *arules* R package [63]. Missing values have handled by deleting those variables in which they were very abundant, and some redundant variables were also eliminated. For this, the function **vis_miss** from the *visdat* R package [64] and **gg_miss_var** from the *naniar* R package [65] have been used.

Bayesian networks

Bayesian Networks are probabilistic graphical models representing the relationships among variables affecting a phenomenon, which can be used for probabilistic inference. For a set of random variables $V = \{X_1, \dots, X_n\}$, that we assume to be discrete or categorical, a standard BN is a model that represents their joint probability distribution *P*, whose graphical part is a *directed acyclic graph* **G**. The nodes of **G** represent the random variables and the directed arcs among the nodes represent the conditional dependencies (not necessarily causal), which are governed by the *Markov condition*, explained below.

It is said that node *A* is a *parent* of node *B* (and reciprocally, that *B* is a *child* of *A*) if there is a directed arc in **G** from *A* to *B*. We denote by *PA(B)* the set of parents of *B* (it is the empty set if *B* has no parents, and we say that it is a "root" node). If there is a "path" from node *A* to node *B*, that is, a concatenation of directed arcs connecting them, we say that *B* is a *descendant* of *A*. ***Markov condition*** can be expressed as follows: "each variable in *V* is conditionally independent of any of its non-descendants conditioning to the state of all its parents". Moreover, *P* can be expressed as the product of the conditional distributions of all nodes given the values of their parents, whenever these conditional distributions exist. This is what is known as **chain rule**, formally expressed as follows (**1**):

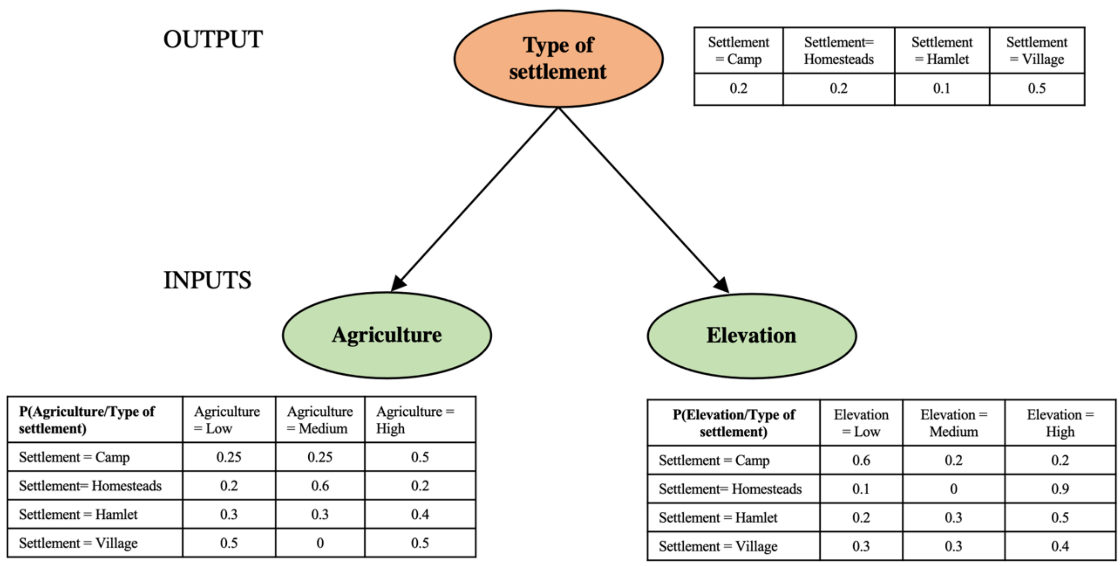
$$P(X_1 = x_1, \dots, X_n = x_n) = \prod_{i=1}^{n} P(X_i = x_i \,/\, PA(X_i)) \qquad (\mathbf{1})$$

for all the possible values of the variables $X_1, \dots, X_n$ [66]. The chain rule allows to obtain the joint distribution of the variables from the conditional probability table (CPT) of each node conditioned to its parents in **G**, and from the marginal distribution of the root nodes. The probability values of these conditional and marginal distributions are the parameters of the BN to be learned from data, jointly with the structure **G**.

We adopt the *hill climbing greedy search-and-score* structure learning algorithm to learn **G** [53,66]. This algorithm explores the space of the directed acyclic graphs by single-arc addition, removal, and reversals, to find the structure that maximizes the score function. We will consider two different score functions: *Bayesian Information Criterion* (BIC) [67], and *Akaike Information Criterion* (AIC) [68], both based on the logarithm of the likelihood function but with a term that penalizes for complexity.

Since AIC penalizes less, using this score leads to learned Bayesian networks with more connected structure **G**. The parameters are estimated by using the *Maximum Likelihood Estimation* (MLE) method, as usual in statistics.

Once the predictive model is learned from the data, it can be used to make inferences. Given the evidence corresponding to the values of some of the variables (*input*), a value can be predicted for another of the variables we are interested in (*output*), which will be the most probable value conditioning to the evidence, following the *Maximum A Posteriori* (MAP) criterion. Let us show it with an example of the BN of **Figure 1**, where the input variables are **Agriculture** an **Elevation** and the output (or class) variable is **Type of settlement**, and each of them have different values: Agriculture has three values (Low, Medium, High); Elevation also has three values (Low, Medium, High); and Type of settlement has four values (Camp, Homesteads, Hamlet, Village). For the input variables we have the CPTs (conditioning to their parent in **G**, which is **Type of settlement**), and for **Type of settlement**, which is a "root" node, we have the table of the marginal distribution.



Settlement = Camp	Settlement= Homesteads	Settlement = Hamlet	Settlement = Village
0.2	0.2	0.1	0.5

P(Agriculture/Type of settlement)	Agriculture = Low	Agriculture = Medium	Agriculture = High
Settlement = Camp	0.25	0.25	0.5
Settlement= Homesteads	0.2	0.6	0.2
Settlement = Hamlet	0.3	0.3	0.4
Settlement = Village	0.5	0	0.5

P(Elevation/Type of settlement)	Elevation = Low	Elevation = Medium	Elevation = High
Settlement = Camp	0.6	0.2	0.2
Settlement= Homesteads	0.1	0	0.9
Settlement = Hamlet	0.2	0.3	0.5
Settlement = Village	0.3	0.3	0.4

Figure 1. Example of a BN to predict the type of settlement. Type of settlement (output, orange), agriculture and elevation (inputs, green).

If the evidence is that **Agriculture** = High and **Elevation** = Low, which is the prediction given by the model (BN) for the class variable **Type of settlement**? We must compute

$$P(\text{Settlement} = \text{Village}/\text{Agriculture} = \text{High}, \text{Elevation} = \text{Low})$$
$$= \frac{P(\text{Settlement} = \text{Village}, \text{Agriculture} = \text{High}, \text{Elevation} = \text{Low})}{P(\text{Agriculture} = \text{High}, \text{Elevation} = \text{Low})} \qquad \mathbf{(2)}$$

For the numerator, by using the chain rule:

$$P(\text{Settlement} = \text{Village}, \text{Agriculture} = \text{High}, \text{Elevation} = \text{Low})$$
$$= P(\text{Agriculture} = \text{High}/\ \text{Settlement} = \text{Village})\ P(\text{Elevation} = \text{Low}/\ \text{Settlement} = \text{Village})\ P(\text{Settlement} = \text{Village})$$
$$= 0.5{\times}0.3{\times}0.5 = 0.075$$

And in the denominator, we also use the chain rule with the four summands (one for each value of Type of settlement):

$$P(\text{Agriculture} = \text{High}, \text{Elevation} = \text{Low})$$
$$= \mathrm{P}(\text{Agriculture} = \text{High}, \text{Elevation} = \text{Low}, \text{Settlement} = \text{Village})$$
$$+\ \mathrm{P}(\text{Agriculture} = \text{High}, \text{Elevation} = \text{Low}, \text{Settlement} = \text{Hamlet})$$
$$+\ \mathrm{P}(\text{Agriculture} = \text{High}, \text{Elevation} = \text{Low}, \text{Settlement} = \text{Homesteads})$$
$$+\ \mathrm{P}(\text{Agriculture} = \text{High}, \text{Elevation} = \text{Low}, \text{Settlement} = \text{Camp})$$
$$= 0.5{\times}0.3{\times}0.5\ +\ 0.4{\times}0.2{\times}0.1 + 0.2{\times}0.1{\times}0.2 + 0.5{\times}0.6{\times}0.2$$
$$= 0.075 + 0.008 + 0.004 + 0.06 = 0.147$$

Then, by replacing in (**2**) we obtain the probability of Type of settlement = Village conditioned to the evidence that Agriculture = High and Elevation = Low

$$P(\text{Settlement} = \textbf{Village}/\text{Agriculture} = \text{High}, \text{Elevation} = \text{Low}) = \frac{0.075}{0.147} \simeq 0.5102$$

And analogously with the other values of Type of settlement,

$$P(\text{Settlement} = \textbf{Hamlet}\ /\text{Agriculture} = \text{High}, \text{Elevation} = \text{Low}) = \frac{0.008}{0.147} \simeq 0.0544$$

$$P(\text{Settlement} = \textbf{Homesteads}\ /\text{Agriculture} = \text{High}, \text{Elevation} = \text{Low}) = \frac{0.004}{0.147} \simeq 0.0272$$

$$P(\text{Settlement} = \textbf{Camp}\ /\text{Agriculture} = \text{High}, \text{Elevation} = \text{Low}) = \frac{0.06}{0.147} \simeq 0.4082$$

Since the probability of **Type of settlement** = Village conditioning to the evidence is the maximum of the four probabilities, by the MAP criterium the prediction for **Type of settlement** provided by the BN, given the evidence, is Village, with a *confidence level* of 0.5102.

We have selected the method of Bayesian networks for this study because of its advantages over other machine learning methods:

i. BNs are "white boxes", that is, they are interpretable models that can be explained in understandable terms and that transparently describe the relationships and patterns between the variables involved, clearly show how predictions are obtained and what are the influential variables, and help generate insights and perspectives [69–71].
ii. Their character of graphic models that is given by the *directed acyclic graph*, together with the *Markov condition* and the *Chain rule*, which allows to obtain the joint probability distribution of the variables of the model (and, therefore, any other probability) from the conditional probabilities of each node to its parents [72], make these probabilistic models a versatile, useful, and unique methodology in the current landscape of ML models.

This methodology is gaining popularity in very different fields of application for the same reasons. Just to mention a few examples, they have been used in public health evaluation [73], for risk assessment with emerging diseases [74], for medical diagnosis [75], in the Intensive Care Unit to predict survival probabilities [76] and for the criminal profile of forest arsonists [77]. Although some previous studies have already applied BNs to address archaeological questions , they have generally relied on "expert knowledge" rather than "data knowledge", which is our approach. **Figure 2** represents the three discussed approaches to learning BNs: classical statistics, expert-based ML and data-driven ML, from left to right.

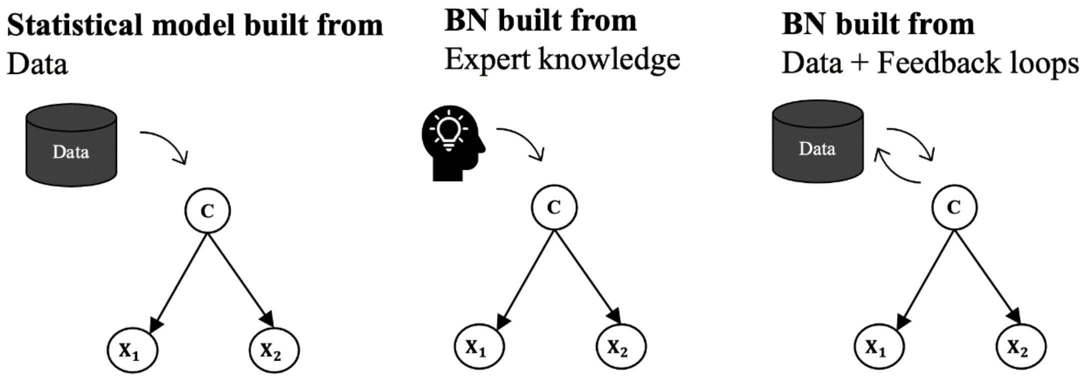


Figure 2. Different general approaches for building Bayesian networks.

As we can see in Fig 2, BNs can be built from expert knowledge, which implies that the researcher that designs the model does form the basis of her/his prior background, expertise, approach, etc. Conversely, BN can be data-driven and that means that the model is learned from the dataset and is relearned every time that new data is available.

Implementation

Exploratory Data Analysis

Our analysis starts studying all potential binary pairings among all variables. We define the very idea of "relationship" in terms of statistical association, and we measure it in terms of association strength in a contingency table through Cramer's V test [83] (**CramerV** function of the *DescTools* R package [84]). In this way, we offer a preliminary scanning of the parametric space to individualise those statistical relationships between ecological features and social decisions that appear most promising, i.e., that may have the greatest predictive and/or explanatory power to understand how features of settlement location may have influenced social decisions and economic strategies, and vice versa (S5 Table). Additionally, we have represented graphically the joint distribution of those pairs of variables that we have found a large association using the **balloonplot** function of the R *gplots* package [85].

With these functions, we have rigorously tested that not all variables are necessarily related to others, nor they have the same predictive/explanatory strength. In fact, only the 3% of the binary associations explored (n=226) had a relevant statistical strength, while 21% did not show any traces of potential explanatory value. Small strength values were the most common (57%). For instance, in our dataset, the size of the community appears to be statistically not binary related with most ecological factors, such as distance to coast, precipitation, etc., nor to social strategies like fishing or not fishing. Similarly, other variables regarding social organisation, like community and domestic organisation, are also not binary related to settlement area factors including slope and intensity of annual precipitation.

Conversely, we have also identified relevant statistical binary associations with high explanatory values (**Figure 3**). For example, the type of settlement is binary related to variations in soil net primary productivity: we can observe that bigger settlements appear located in areas where soil net primary productivity can have medium or high values, but fast never low values. On the contrary, small hamlets and homesteads settlements favour locations with low variability in soil net productivity. Another example is the relationship between animal husbandry and location, which suggests that communities decide to intensify husbandry in areas of relatively high elevation, where agriculture can be less successful.

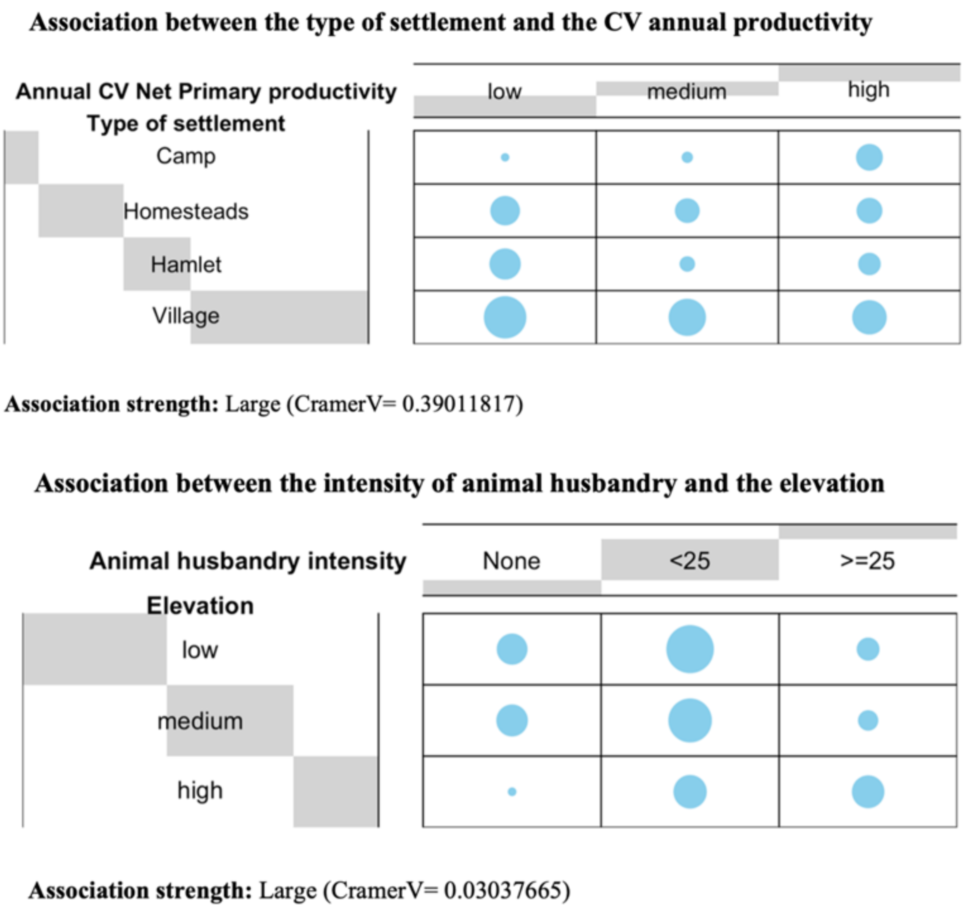


Figure 3. Some examples of binary associations found in the exploratory data analysis.

Model design

The advantages of BN methods allow asking two fundamental questions to be approached inductively and probabilistically.

Q1) Do ecological features of settlement location and/or social organisation constrained the type and intensity of subsistence strategies? We have explored this question by analysing the probabilities of two competing hypothesis:

- Ecological factors constrain the subsistence strategy (Input: environmental characteristics / Output: subsistence strategies),
- Social organisation constrains the dominant form of subsistence strategy finally adopted by the community (Input: social organisation / Output: subsistence strategies).

Q2) Do ecological features of settlement location and/or the type and intensity of subsistence strategies constrained social organisation? We have explored this question by analysing the probabilities of three competing hypothesis:

- Ecological factors constrain the way the community is socially organised (Input: environmental characteristics / Output: social organisation),
- Ecological factors constrain social/economic decisions made by the community (Input: environmental characteristics / Output: social decisions),
- The particular type of social organisation and the subsistence strategy finally adopted constrain social/economic decisions made by the community (Input: social organisation and subsistence strategies / Output: social decisions).

This definition of just a handful of restricted scenarios has allowed us to reduce the dimensionality of the parametric space and obtain meaningful results with a minimum of computational run-time. By considering only a reduced set of scenarios, we intend to group calculations into meaningful blocks. Some other scenarios could have been explored, but this is something that will be developed in forthcoming essays. We have built three structurally different networks for each scenario to determine which model has the greatest predictive and explanatory capacity:

- Models *A type* (*Binary Relevance)*: it is used to predict one output at a time, from all the input variables, so it is made up of as many BNs as output variables we have, each one with all the input and a single output variable. We have experimented with two different kinds, depending on the type of BN that is implemented:
    - Naïve Bayes (Model A-NB): It has a fixed structure, which is not learned from the data, with a directed arc from the output variable to each of the inputs, and no more.
    - Augmented Naïve Bayes (Model A-ANB). Directed arcs are allowed between the input variables, which are learned from the data.
- Model *B* consists of a single BN that contains both the input and (all) the output variables and allows them to be predicted all at the same time. Its structure is learned from the data with the only restriction that there can be no directed arcs from any input variable to any of the output variables. It is then a diagnosis-type predictive model.

These models, learned from the training set according to different restrictions, will entail some advantages and disadvantages for each, as specified in **Table 3**. See also **Figure 4** for a simple example of the three types of structures illustrating the constraints on directed graphs with which they are built.

The ultimate objective of building three different models is to compare model structures and evaluate if correlations among variables are important to consider when building a model and provide relevant information for understanding the socio-ecological systems examined.

	MODEL A: BINARY RELEVANCE (one output at a time)		**MODEL B (all outputs at once)**
	NB	**ANB**	
Description	Naïve Bayes (NB)	Augmented Naïve Bayes (ANB)	Unrestricted diagnosis-type BN
Structure learning algorithm	Fixed structure with arcs from output to inputs (black box)	Hill-climbing with AIC and BIC scores. Arcs from output to inputs mandatory (white box)	Hill climbing with AIC and BIC scores. Arcs from inputs to outputs forbidden (white box)
Purpose	Prediction	Prediction and explanatory (relationships between input variables)	Predictions and explanatory (relationships between input, between output, and input-output variables)
Advantages	Conceptual simplicity and good balance between simplicity and predictive power. Robust against unlikely evidence	Encodes the relationships between inputs, for each output separately, keeping the design relatively simple	Encodes the relationships between inputs, between outputs and between inputs and outputs. Single model in which relations between variables are not forced
Disadvantages	Ignores the correlations between inputs and between outputs (a different model is built for each output)	Less conceptually simple than NB, and like it, ignores the correlations between outputs (a different model is built for each output). Sensitive to unlikely evidence	More complex design than the others. Sensitive to unlikely evidence

Table 3. Description and main characteristics of the three types of BNs.

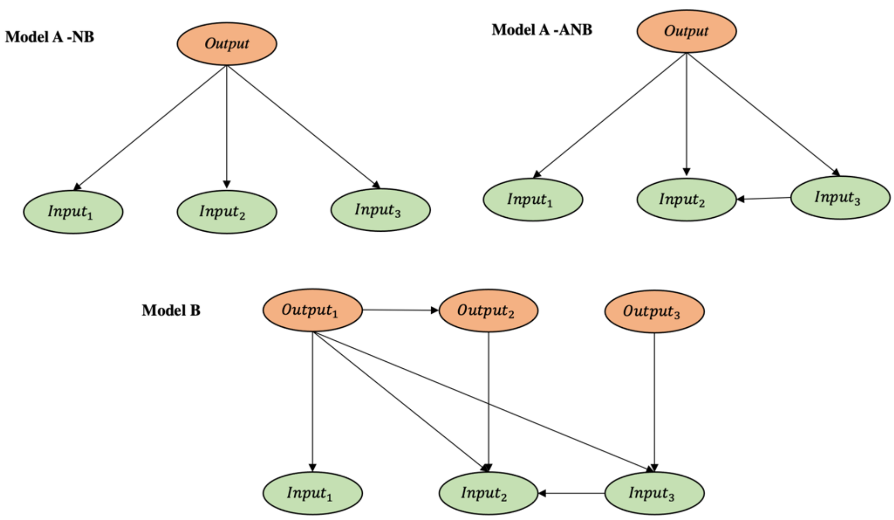


Fig 4. Examples of the structures of the three types of BNs in Table 3. Outputs (orange) and inputs (green).

The models have been built using the R package **bnlearn** [86], which implements structure and parameter learning. To learn the structure of Model A – ANB we used the score-based structure learning algorithm implemented in the **hc** (hill-climbing) function was used, and to make the predictions we used the R package **gRain** [87].

Model validation

To validate the three models in each of the five scenarios, and to be able to select which one has the highest predictive value, we have used statistical accuracy measures as a performance metric using a k-fold cross-validation procedure with $k = 5$. In each scenario, the dataset formed by the input variables and the output variable(s) was randomly divided into five similar folds, using four of them as a training subset to learn the model and the fifth as a test set to make predictions to evaluate the predictive power of the model by calculating its accuracy. The number of outputs for each fold depended on whether the Model was A or B. This process has been repeated k times, each time changing the test set training and, consequently, the training set. In this way, for each scenario and model, we obtain $k = 5$ estimates of its statistical accuracy.

First, we have compared Model A-NB with Model A-ANB. A standard statistical hypothesis test has been used based on the two samples of paired values of their accuracies. To decide whether to use the parametric paired t-test, or the non-parametric paired Wilcoxon signed-rank test, we first performed a Shapiro-Wilk goodness-of-fit normality test for the difference. In case of models *A,* we have privileged those with the greatest predictive capacity, to be compared with the relative Model *B* to make the best possible prediction.

Once the model with the highest accuracy is selected, the *strength* of the probabilistic relationships between the model variables expressed by the arcs of the BN is quantified through the function **arc.strength** (implemented in the *bnlearn* R package), producing a result in form of a p-value for a conditional independence test: the lower the p-value, the stronger the relationship. On the other hand, Model B has been always used for its explanatory habilities, since it is the only network typology that allows correlations between inputs and inputs and between outputs and outputs. Results of the validation process are depicted in S6 Table.

Results

As we already knew from our initial exploratory analysis, not all variables -ecological and social/economic- have any explanatory contribution on the other. Values of output variables are hardly predictable from input variables. This result does not go in line with the prior traditional hypothesis that implies that human behaviour is necessary fitted to local ecological conditions. Our results (**S7 Table**) suggest that the relationship between human action and landscape is far more complex than that: different behaviours can be practised, and different social decisions can be made at different ecological, climatic, and topographical contexts.

The influence of ecological factors on the subsistence strategies adopted

When we assume the independence between the inputs conditioned to the values of the output (Model A. Naïve-Bayes learning algorithm), our investigation suggests that ecological conditions effectively constrain hunting. That is to say, the dominant landscape type, the elevation of the site catchment area, its annual precipitation (average and variation), its annual temperature (average and variation), the soil productivity (average and variation) and distance to the coast have a high impact on the variations of hunting relative predominance among alternative ways of acquiring percentage of subsistence. The same impact on gathering is limited to the landscape and the soil productivity variation. It can be surprising at first to see that most ecological factors have also direct influence on fishing, except slope and soil productivity variation. This result goes in line with the study conducted by Ahedo et al. (2021) in which they identified fishing with the role of risk-mitigation function that small-scale farming communities adopt in times of scarcity [18]. Therefore, fishing would not be related to the landscape characteristics, but to the internal dynamics of the community [88,89]. Instead, hunting and gathering would have been part of the mixed farming strategy complementary to animal husbandry and agriculture.

In the case of animal husbandry, the impact of all ecological, climatic, and topographical factors –except distance to the coast- on its relative predominance respect to the alternative subsistence ways is very high. This high correlation was expectable since small-scale communities practising herding may practice seasonal vertical mobility to maximise herd production and survivorship in communities with mixed economies. Generally, during the late spring and early autumn animals are moved in the mountain whereas winters are located in the lowlands plains. This practice was probably already present in the early Neolithic, for example [90,91], and there is an important corpus of ethnographical data supporting the archaeological data [92,93] used to support the archaeological data.

The comparatively high impact of environmental conditions on the relative predominance of hunting, gathering and husbandry contrasts with the low relative importance of landscape factors on the predominance of agricultural subsistence. This last result does not mean that environmental factors have no causal impact on variations on agricultural predominance relative to the other subsistence ways, but this impact is far lower than in the case of hunting and husbandry and, hence, the predictability of relative importance of agriculture in terms of ecological conditions is far lower than in the other cases. Results suggest that human communities can decide to increase their farming effort in relation to other strategies (e.g., hunting, gathering, etc.) in landscapes with any elevation and/or slope, hence their low predictability value. This is a result specially significative because there is a long-standing tradition in archaeological site settlement studies of placing considerable importance on ecological characteristics to predict the placement of agricultural places [94–97].The underlying assumption is that by modelling the most suitable landscape for productive economic strategies, the most probable settlement and occupation locations can be predicted. However, recently, some studies have emphasised the lack of direct and linear correlation between farming and the ecological characteristics of the settled area. For instance, a recent study of Vidal-Cordasco and Nuevo-López (2021) evidences that early Neolithic communities in Iberian Peninsula expanded their ecological niche breath with the adoption of farming practices whereas Mesolithic populations practicing hunting and gathering would have been more restricted because of the ecology [98]. When expanding the production area, more ecological and landscape diversity enter into the catchment area, and the relevance of particular factors diminishes.

Variations in soil natural productivity have large impacts on all subsistence strategies, except agriculture. It contradicts traditional hypotheses suggesting that a prior high soil productivity is paramount for farming practices [99,100]. Our analysis suggests the relevance of social decisions for reducing or expanding human mobility and/or the possibilities for increasing labour investment independent of increasing technology efficiency or modifying the group internal organisation –social relations of production. And this relationship holds even when soils have less productivity. This result demonstrates the importance of human agency and intentionality on modifying the environment even when more suitable location -in this case, more productive soils- would have been available.

Our study also asserts that the total independence of ecological, climatic, and topographical factors among them is a hardly defendable assumption. Temperature average and temperature variation are correlated in most cases, in the same way as in the case of precipitation and soil productivity. Settlement elevation and slope are correlated in many cases. We have used the Augmented Naïve Bayes algorithm to build the interrelations among all possible ecological/climatic/topographical inputs on each kind of subsistence strategy (**Figure 5**). This analysis suggests that distance to the coast, temperature and precipitation are not totally independent among them. The same can be defined for slope and elevation, and soil productivity average and variation. The kind of landscape is mostly independent from the rest factors, although some dependence can be proved with average precipitation and/or soil productivity. In the same way, precipitation and soil productivity seem to be indirectly related will be not totally independent.

Figure 5. Model Augmented Naïve Bayes of the influence of the environment on subsistence strategies. Dependence between ecological variables (inputs, green) and subsistence strategies (outputs, orange). The relationship among ecological factors when we predict the outputs agriculture, animal husbandry, hunting and fishing is exactly the same (the BN of agriculture is depicted as example) and, when we predict gathering, we can observe slightly differences in how climate variables are interrelated.

Considering these dependencies among input factors, the accuracy of social and economic predictions critically diminishes, because non-linear relationships affect probable consequences of human prior knowledge about the area they may settle. This result suggests the low reliability of traditional hypothesis suggesting direct and linear landscape determinism.

Up to now we have worked with single outputs. We have not yet considered the obvious non-independence between hunting, gathering, fishing, agriculture, and husbandry. After all, what we are considering is the percentage of total subsistence a human group decides to acquire using different alternative strategies. **Figure 6** and **Table 4** show dependencies between all strategies. The preference for animal husbandry plays an intermediate role: on the one hand, it is related to foraging activities and, on the other, with agriculture. The preference for hunting and gathering are clearly related with animal husbandry, because monthly mean and monthly variation of precipitation affect them in the same way. The preference for fishing is related to the preference for animal husbandry (and indirectly to hunting and gathering) because of the high incidence of distance to the coast. Obviously, settlements with highest proportion of subsistence acquired by fishing are those the nearest to the coast. Our results also indicate a non-negligible influence of distance to the coast to the preference for animal husbandry and agriculture. The preference for this last strategy is clearly the less affected by landscape conditions, in the sense that practicing agriculture depends on social issues more than on local characteristics of the area of production.

In this scenario we predicted the correlations among the ecological characteristics (inputs) and the subsistence strategies (outputs).

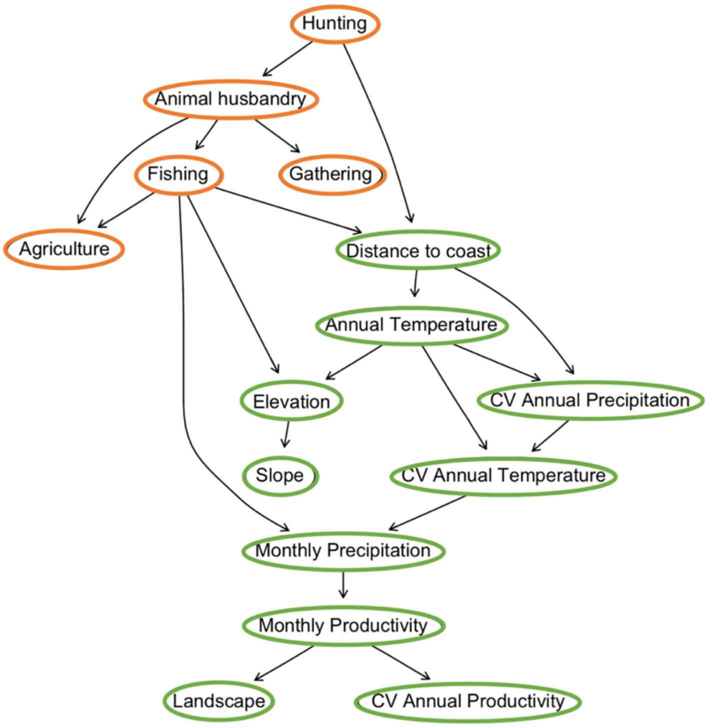


Figure 6. Final Model B exploring the influence of the environment on subsistence strategies. In this scenario we predicted the correlations among the ecological characteristics (inputs) and the subsistence strategies (outputs).

Input	**Output**	**Relationship**	**p-value**	
Landscape	*Agriculture*	Animal husbandry - Fishing	9,03E-09	***
Distance to coast	*Animal husbandry*	Fishing – Distance to coast	1,54E-07	***
Elevation	*Hunting*	Hunting – Animal husbandry	6,59E-06	***
Slope	*Gathering*	Animal husbandry - Agriculture	6,72E-06	***
Annual mean temperature	*Fishing*	Fishing - Agriculture	5,12E-04	***
Coefficient of variation temperature		Animal husbandry - Gathering	9,11E-04	***
		Fishing - Monthly mean precipitation	2,15E-03	***
Monthly mean precipitation		Fishing - Slope	3,19E-03	**
Coefficient of variation precipitation		Hunting - Distance to coast	4,37E-02	*
Monthly mean net primary production				
Coefficient of variation net primary production				

Table 4. Final correlations of Model B exploring the influence of the environment on subsistence strategies. They correspond to the graph depicted in Fig 6 and only relationships statistically significant are included and their p-values are classified as follows: 0.05-0.01 = *; 0.01-0.001 = **; <0.001 = ***.

Although all landscape characteristics seem to be connected among them, our results for this scenario show the higher influence of precipitation on all forms of subsistence strategy, more than any other ecological, climatic, or topographical factor.

The influence of ecological factors on the way the community is socially organised

When we assume the independence among ecological, climatic, and topographical factors, our analysis suggests that landscape, climate factors (average and variance of temperature, average precipitation) and soil productivity (average and variance) may affect the type of settlement (camp, homestead, hamlet, village). Naïve Bayes results also suggest that the size of the community can be constrained by the variance of annual precipitation, the organisation of the community by the distance to the coast and the annual mean temperature and, the organisation of the household by the elevation, the variance of temperature and the variance of soil productivity.

The dependencies between ecological, climatic, and topographical factors do not modify significatively this global image as we can observe in **Figure 7**.

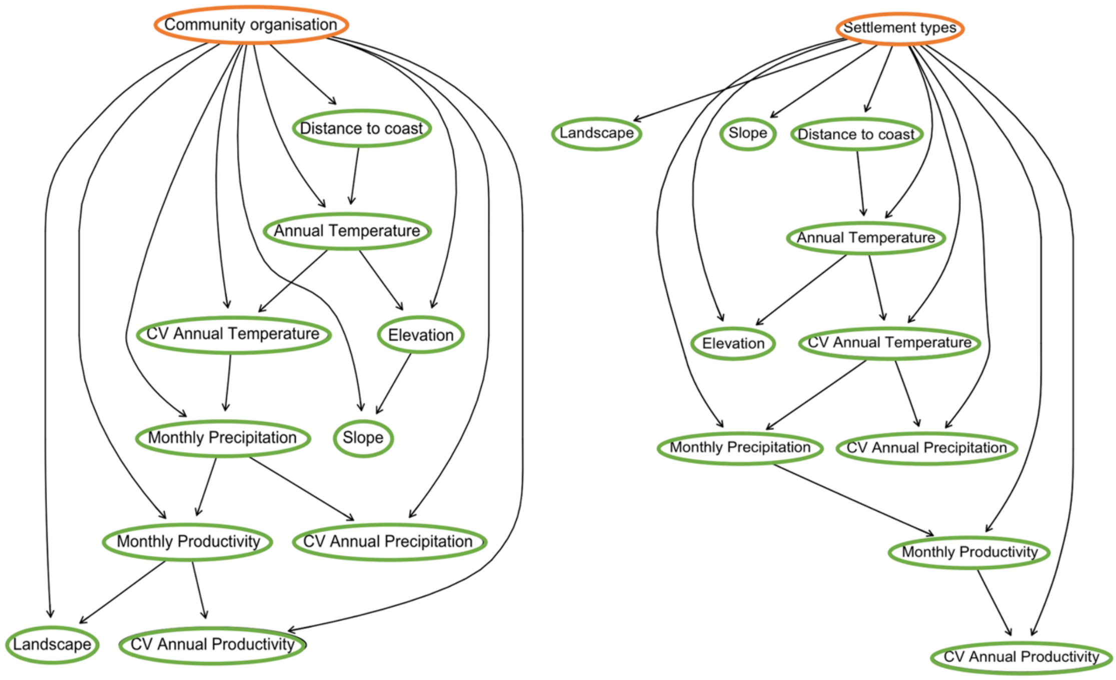


Figure 7. Bayesian Networks of Model A-ANB exploring the relationship between the environment and the social organisation. Dependence between ecological variables (inputs, green) and social organisation (outputs, orange). There are slight differences between the BNs designed for each output. For instance, in the BN of type of settlement, landscape is not related to monthly mean precipitation (as it is to the BNs of size of community and household organisation) or monthly mean productivity (like community organisation).

It is important to note that the dependencies among ecological, climatic and topographical factors, as discovered by the machine learning algorithm, do depend on the output. Therefore, dependencies are slightly different than those detected in the case of the influence of landscape on subsistence strategy. In general, we still observe that climatic factors are correlated. But now, topographical factors (elevation, slope) appear to be independent between them, probably because it is the factor with the less relevance to predict social organisation. Landscape, which has relevant strength to predict the size of community and settlement type, appears to be non-related with other input factors of this scenario. The remaining factors show relevant dependencies.

The lack of dependencies between social organisation categories and attributes, explain the lack of accuracy in Model B predictions. This lack of dependencies is analysed in detail in later.

The influence of ecological on social/economic decisions made by the community

When assuming the independence of ecological, climatic, and topographical features, we have found relevant influence of landscape on the decision of doing nothing to increase resources in face of scarcity. This kind of behaviour has been described by prior authors as 'supply-induced scarcity' [25,27,101] in which communities reduce their food intake and suffer some periods of hunger. In the monographies collected in the eHRAF database, we identified this behaviour in five communities: the Anaguta [References Supporting Information 98, 99], the Chucki [References Supporting Information 150], the Lovedu / Balobedu [References Supporting Information 267, 268], the Maasai [References Supporting Information 273, 277] and the Mambila / Mambilla [References Supporting Information 281, 282]. For example, Spencer (1988) described thisthis social decision in the Maasai of Matapata as:

> "*The problem of drought is never quite resolved, but as Matapata view their mode of adaptation to their ecological nicge, the benefits for those who survive and thrive are prefereable to any alternative*". [References Supporting Information 273]

In our results, this type of decision seems to relate to the kind of landscape, given that some landscape types (tundra, desert among them) are invariable.

The annual mean of temperature has relevance on the decision towards diversifying the acquisition of resources. These are cases in which farming communities decide to diversify their economic basis in periods of very high or very low temperatures by introducing new foodstuffs to increment food security (i.e., mixed farming). Slope and soil productivity are relevant in the decision towards foraging intensification, that is when diminishing returns from agropastoral practices stimulate the transfer of labour force and time of work to alternative, more generic activities like foraging (hunting and gathering). Mean precipitation and mean soil productivity have relevant effect on the decision towards socially moving (migration). This result is suggestive because it shows that the causes of temporal migration are more related with the deficit in the aggregated annual volume of production than with the annual irregularity. Finally, the elevation of settlement is relevant to predict the decision of reciprocal giving of resources to other households within the community.

Dependencies between ecological/climatic and topographical factors are very similar as those obtained in precedent scenarios. Their differences are not meaningful as we can observe in **Figure 8**.

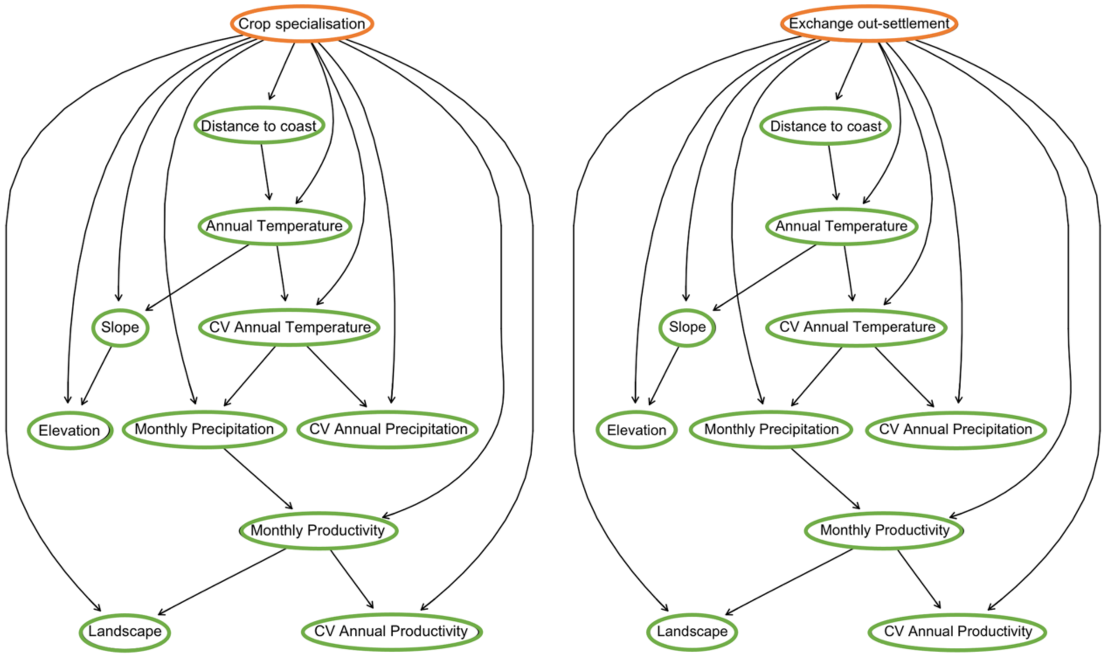


Figure 8. Model A-ANB investigating the relationship between the environment and social decisions. Dependence between ecological variables (inputs, green) and social decisions (outputs, orange). The relationship among ecological factors when we predict all the outputs of Social decisions, except for the category 'exchange out-settlement', is exactly the same (the BNs of crop specialisation and exchange out-settlement are provided as example). In the BN of exchange out-settlement, we can observe differences in the ecological factors of landscape and distance to coast.

When considering the dependencies among ecological, climatic and topographical, the predictability of the outputs does not vary significatively. However, we have detected an increase in the predictability of permanent migration based on the impact of average temperature. That means that this is not the only factor affecting the decision to move permanently, but a non-linear aggregated effect of all ecological/climatic/topographical.

Our analysis of Model B has not detected any contribution from the dependencies among social decisions. That is to say, the complementarity between some of those decisions (i.e., between resource diversification, storage and foraging intensification, or between temporal migration and transhumance). We have not found any impact of ecological, climatic, and topographical factors on crop specialization, storage, transhumance, and exchange (both within and between communities).

The influence of social organisation variability on the dominant form of subsistence strategy

Although it could be expected some degree of non-independence between social organisation variables (input), our analysis using Augmented Naïve Bayes proves that most attributes we have labelled as "social organisation" are not related among them when they are conditioned to subsistence strategies. That is, no relationships appear in our datasets among size of population, structural diversity of settlement, relevance of kinship ties, etc. The graph generated by the algorithm shows the lack of interrelationships between inputs (**Figure 9**).

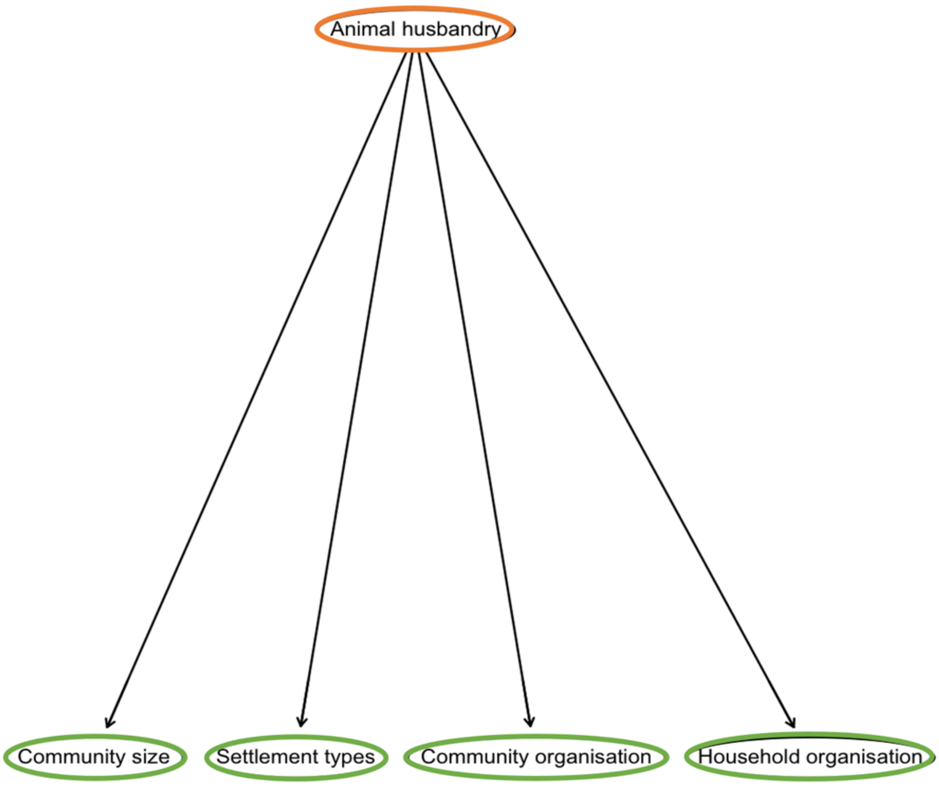


Figure 9. Model A-ANB exploring the relationship between social organisation and subsistence strategies. Dependence between social organisation (inputs, green) and subsistence strategies (outputs, orange). The relationship among input variables is the same for all the BNs produced for all the outputs examined.

In these circumstances, we have only found some low degrees of predictability between the mean size of the community and the differential predominance of gathering (Naïve Bayes, assuming conditioning to the output), and between settlement type, community organisation and predominance of agriculture (Augmented Naïve Bayes). Those results are obvious if we consider that the higher the number of people in the community, the more diverse will be its structure and organisation, and the greater its dependence to subsistence strategies that may generate greater volumes of subsistence. On the opposite, the lesser the size of the human group, the more efficient will be generalised gathering activities. This lack of association between the type of settlement and the size of the community is also supported by prior studies [102]. We have not found any significant impact of the forms of social organisation on the relative proportion of subsistence acquired through hunting, husbandry or fishing activities. The relationship between husbandry and fishing, discovered in the Model B of this scenario is also consequential given the structural compatibility between these strategies.

In most cases, the relative proportion of subsistence acquired using different strategies seems to be independent on the different possible ways of socially organizing the community (size of community, settlement structure and diversity, family organisation, kinship ties, etc.). In our dataset we find instances of different forms of social organization associated to any subsistence strategy.

The influence of social organisation and the subsistence strategy finally adopted constrain social/economic decisions made by the community

In the previous scenario we have concluded that the relative proportion of subsistence acquired using different strategies seems to be independent on the different possible ways of socially organising the community (size of community, settlement structure and diversity, family organization, kinship ties, etc.), and vice versa. We then may expect that social organisation *and* subsistence strategy may have low incidence to explain the social and economic decisions a community may adopt in face of scarcity.

This previous result contributes to the assumption of independence among the different inputs. In such conditions, the high relevance of agricultural subsistence directly affects the success of economic life and the absence of any decision to intensify. On the other hand, agriculture also affects positively the exchange within settlement. Husbandry is also a condition for the absence of any form of intensification. In fact, prior studies highlight the role of animal husbandry and transhumance as a risk-management activity which would be complementary to other practices such as farming [91].

Most interesting is the Naïve Bayes result of the influence of fishing on the intensification of foraging resources, which goes in line with Ahedo et al.'s study in 2021 that argues that fishing would have played a 'nexus' role between primary economies (agropastoralism) and mixed economies (hunting and gathering) [18]. Also relevant is the influence of the kinship organization of the community (clan, non-exogamous) on resource diversification. The type of settlement constrains the probability to decide for crop specialisation.

Discussion

Our analysis shows the intrinsic non-linear and non-monotone nature of the relationship of ecology, social behaviour, and economic strategies. We are not the only ones arguing for the complex and non-linear nature of the relationship between the environment and people decisions. In this study, however, we have partially tested how communalities between apparently different small-scale farming societies emerge when we formalize some of the environmental factors that may have affected social decisions. To address the problem of the variable predominance of alternative subsistence strategies in different social, economic, and ecological contexts, we have analysed how ecological features of settlement location and/or social organisation may have constrained the type and intensity of subsistence strategies. Results show that some landscape characteristics of the settlement area may influence indirectly the type of subsistence strategy that the community would have practised. For example, in our database, an environment characterised by a landscape of grassland, with low and stable productivity soils, located at a long distance from the coast, at high elevation and slope, with low average temperatures but highly variable annually, high average precipitation and highly variable annually, we should expect that not any human group would practise gathering or fishing. On the other hand, in an environment characterised by a landscape of forest, with low and highly variable productivity of soils, located at a short distance from the coast, at medium elevation and slope, with medium average temperatures but highly variable annually, low average precipitation and highly variable annually, we should expect that not any human group would practise hunting nor fishing. Therefore, different strategies are more probable in specific landscapes than others.

Our results indicate that this situation is only true for foraging strategies - hunting, gathering, and fishing – since it has not been possible to obtain a solid prediction for husbandry and agriculture from landscape characteristics. This can be a consequence of the importance of diverse social behaviours in this two food acquisition strategies. The hypothesis has been tested comparing the diverse forms of social organisation that different small-scale farming communities may adopt. Our results suggests that the type of settlement, community organisation and the number of inhabitants play a major role in most social decisions with economic relevance. For example, when a small human community of less than 200 people live at a temporal camp, with a social organisation based on small households and clans, it is expected the adopted a subsistence strategy based on animal husbandry, complemented with hunting, and gathering. When assuming the non-independence between social organisation and subsistence strategies, the predictability of gathering diminishes drastically, and increase the probability of agricultural practice.

On the other hand, when a small human community of less than 200 people live at a permanent isolated homestead, with a social organisation based on small households and clans, our model predicts the relevance of agricultural practices, and fishing, and the diminution of animal husbandry. It is significative that only a modification in the input (from temporal camp to permanent isolated homestead) brings about a so important modification on prediction. When modifying the size of the population and considering permanent isolated homesteads of more than 200 people, also organised in terms of small households and clans, the prediction of heavy impact of agricultural practice and the low impact of animal husbandry and hunting holds. Fishing and gathering disappear in this last scenario.

These results demonstrate the importance of considering the type of organisation, settlement and amount of people for predicting the most probable location of the settlement of agropastoral communities, whilst the environmental conditions are more relevant for defining foraging communities. Importantly, social decisions that can be adopted in face of scarcity seem to be too variable and independent to the local conditions of landscape or the social organisation of the community. This result is very relevant to understand socio-ecological dynamics: human groups can build different kinds of social organisation independently to the local characteristics of their landscape.

Our investigation has also allowed to predict how *both* the environmental characteristics and the type of subsistence strategies influence significatively the way that community can be socially and politically organised. For instance, according to our model, a settlement located away from the coast in an elevated grassland with high slopes, with low but variable temperatures and high and variable precipitations through the year, affecting negatively on soil productivity, we can predict that a community with a small extended organisation at domestic level and not organised in clans is the most probable. Additionally, we have obtained differences depending on what model we use for prediction: when we assume the independence among ecological variables, we predict a community of more than 200 inhabitants living in homesteads (isolated domestic units) whereas according to Model B what results is a predicted a settlement with less than 200 inhabitants living in a camp (temporary location). Besides the amount of people, all models agree that this particular case can be related to a circumstances characterised by mountainous location, in which small, disperse and temporary settlements are the most probable.

When we predict the organisation of the community in a completely different topographic and climatic characteristics (located close to the coast, with high temperatures through the year, low precipitations but variable and low soil productivity but very variable), we observe that the site would be highly probably a village and not organised in clans. When the independence among inputs is assumed (Naïve Model), we predict a large extended household organisation and a small amount of population. The number of inhabitants increases (above 200 inhabitants) in Augmented Naïve Model and, that is, when the relationships among inputs are allowed. Conversely, in Model B a population of less than 200 with small extended organisation in predicted.

Conclusions

This paper is based on observed communalities among 173 trans-historical and cross-cultural dataset of small-scale farming societies, expressed in probabilistic terms to be able of predict social behaviour from environmental and landscape features.

Although the database is comparatively small for typical Machine Learning applications, it should take into account that it is complete for the social domain of small-scale farming societies. Those are the only well documented ethnographic cases existing in the literature. The dataset could have been increased including poorly documented cases, with a lot of missing values in the final dataset. The consequences would have been poorer accuracy in generalisations and still low values of precision in predictions. Therefore, we can be fairly confident of the accuracy and plausibility of our main result: the nonlinearity of the particular relationship between what people do to live, and the main features characterising the environment and the landscape where people live. The particular way people acquire their subsistence cannot be predicted without considering how people organise their settlement and their social relations of production. Only the simplest activities, hunting and gathering, are related directly to the environment.

The nature and reliability of calculated generalisations can be used to reconstruct, although partially, how people behave and took social decisions many years ago. Obviously, our results depend on the reliability of the training set used for probability estimations and predictions. In any case, we are not asserting that the past is like the present, but generalisations proved to be true in a great majority of known and well documented ethnographic cases from different chronologies and geographical areas can be considered also plausible of societies having existed in other time periods with similar ecological and environmental circumstances. What we are interested in is to consider the structural relationships between society and nature. The fact that this relationship be non-linear and indirect, affected –but not determined- by human particularity, only makes the reconstruction of prehistoric ways of living more difficult. We rely on the language of probabilities, and Bayesian reasoning, to explore scenarios that were "probable" in the past, although we have not the full evidence.

This study highlights the co-evolutionary process of the environment and small-scale farming communities on shaping their settlement location, economic behaviour and social preferences. In contrast to social groups relying only on hunting, gathering or fishing, human communities with mixed farming economies were more diverse, and therefore individual factors constrained fewer particular forms of living and working. More variables, and not only landscape and environment, should be considered to understand how survival was possible thousands of years ago. For example, our model suggests that animal husbandry could not be limited to a singular niche, but herders could move their flocks seasonally and, therefore, adapt to many different environmental circumstances. In the same line, a especially significant finding was the lack of relationship of the preponderance of agriculture among other subsistence activities with the degree of soil productivity. We hypothesise that in similar manner than herders, farmers could modify their niche by incrementing the labour investment and, consequently, defining the most suitable type of settlement and size of community for this economic strategy. Social decisions such as diversifying the resources produced, migration of people or the exchange of foodstuffs could have played a major role for managing and compensating the resource availability in the community.

The detailed knowledge of landscape conditions by the social group could allow prehistoric communities to predict the probability of success when hunting and fishing. Gathering was not only constrained by what the landscape naturally offered, but the knowledge of the size of the community has also relevant effects on prediction: the lesser the size of the human group, the higher the probability that some part of the total revenue came from gathering the area around the settlement.

We suggest that in prehistory, community organisation was only partially influenced by landscape and environment, in the same way as our ethnographical generalisation has proved. This also applies to social decisions in face of scarcity, which can only indirectly be related with ecological, climatic, and topographical factors. It does not mean that the environment could have no effect at all. We have distinguished some contribution of precipitation average and soil productivity on temporal migration, whereas average temperature seems to have more impact when considering permanent migration. This result can be explained in terms that scarcity generated by precipitation average could short term effects, whereas scarcity caused by variations in temperature have long term consequences.

Beyond landscape influence, social decisions in face of scarcity are also influenced by the kind of dominant subsistence strategy and the way the community is organised. For instance, there is high correlation between agricultural revenue and the exchange of food items between different communities. In the same line, the type of settlement and the probability of social decisions towards increased crop, also constrained the social organisation of human groups. We have not discovered, however, dependencies between the exchange of food between groups and the increase of crop specialisation or between the decision of diversify exploitable resources and foraging intensification.

Methodologically, the main result of this investigation lies on the recognition of the relevance of the independence between input factors, between output factors and between input and output factors. Assuming independence has been the traditional assumption is most socio-ecological investigations. Our analysis signals the misleadingness of this assumption, and the need of considering the way the causal influence of a factor has on another factor to be able to predict how a small farming community may have reacted locally.

Bayesian Networks, the kind of machine learning algorithms used along this paper, show their value for understanding socio-ecological systems. They are useful and versatile "white box" models that clearly describe the relationships and patterns between the variables involved in a phenomenon while providing predictions of the *output* variable of interest and generate new knowledge. The reason why we decided to put it into practice here is to experiment and validate its application in ethnoarchaeological contexts. By building three different learning algorithms, modelled to explore alternatives assumptions and scenarios (Naïve Bayes, Augmented Naïve bayes, Unrestricted Diagnosis Networks), we have demonstrated that not all assumptions have the same predictive and explanatory potential.

With Bayesian Networks it is possible to identify a connection between what we infer that could have happened in the past and the material evidence that this action caused and is observable in the present. However, it should be borne in mind that this study represents a preliminary investigation, since we have worked with a limited number of cases because they were the ones available in the two databases that we have consulted and that followed the requirements set. However, the number of cases should be increased to assess whether the same relationships between variables are still observed. Another aspect that we would investigate in the future is to explore our database with Gaussian or hybrid Bayesian Networks, the latter allow working with both numerical and categorical input variables, while with the Gaussian BN we can only consider continuous input variables. Standard Bayesian networks only deal with discrete/categorical variables and, as consequence, we have been forced to discretize the continuous variables, with the consequent loss of information. Likewise, working with more case studies, continuous data and conditionally Gaussian Bayesian Networks, we would hope to describe better the relationships between variables and identify nuances that with the current model have not been possible.

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3.4.2. **Palacios, O.** & Barceló, J.A. (2023). Survival in prehistory: Disentangling the complexity of dependent relationships. *Journal of Anthropological Archaeology.*

Survival in Prehistory: Disentangling the Complexity of Dependent Relationships

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Abstract

In this study, we will focus on exploring the impact of environmental change and variation on social activities related to the economy that agropastoral groups might have adopted in the face of scarcity. We intend to discuss the particular dependencies –probabilistic relationships and hence, causal relevance- between particular *landscape local conditions,* features of social life related to the *social organization* (type of settlement, number of inhabitants, observed inequalities), the general kind of *subsistence strategy* (foraging and agropastoral resources consumption), and the particular decisions taken to prevent the risk of scarcity (*social decisions*). The discussion in this paper is based on results from a previous study (Palacios et al., 2022), in which we analyzed 173 ethnological examples for statistical dependencies between landscape characteristics, socioeconomic strategies, and social decisions. Using Machine Learning tools such data allowed the construction of a probabilistic interdependency network. In this paper, results are evaluated using modern Niche Construction Theory and compared with general theories on survival in early farming societies.
Keywords: agropastoral groups, social decisions, Machine Learning, Niche Construction Theory

Statements and declarations

This work has not been published previously and is not under consideration for publication elsewhere. Its publication has been approved by all authors. We have no conflicts of interest to disclose.

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1. Introduction

Survival can be defined as the persistence of life despite difficult circumstances. It does not solely depend on the capacities of human individuals, but also on their interactions with their natural surroundings (Piantadosi, 2003). We do not know *how* people survived in the past; however, we have some indirect data about the survival of people in the past: from seeds and faunal remains we know what they ate, from tools and artefacts their technology, from negative and positive structures their buildings. The temporal duration of settlement evidence suggests that people that lived there survived for a determined time interval, from the begin of the settlement to its abandonment. We know they survived but we do not know *why* they did what they did in the way they did. In most studies, survival equals meeting the minimum number of calories of living in the settlement, but this is a simplification of a complex problem. Obviously, the available resources of the environment contributed to survival, but we cannot affirm that those factors *caused* survival. Available technology, available labor force, and the nature of social decisions also contributed.

A *socio-ecological system* can be described as a structure constructed from the interaction among social behaviors (e.g., subsistence strategies or social organization), and ecological (climate or soil productivity) components (Biggs et al., 2021). These interactions are not the result of deterministic linear relationships but complex, dynamic, and interconnected structures with feedback across social and environmental dimensions (Ferraro et al., 2019). In this paper, we intend to analyze some aspects related with the complex relationship between environmental factors and social behavior from the premise that human actions modify the landscape. These concerns have already been approached within the framework of the Niche Construction Theory (NCT) (Laland et al., 1996, 1999; Odling-Smee et al., 1996), which considers the dynamism and co-evolutionary transformations resulting from human decisions in face of human transformations in the environment (Odling-Smee et al., 2003; Laland et al., 2001; Laland & O'Brien, 2010; O'Brien & Laland, 2012). From this perspective, human communities interact –and interacted in the past- and transform their natural setting with their productive and social activities (e.g., organization of labor, preferences for some resources over others), and their intensity varied according to varying circumstances and scenarios. Our approach in this paper is theoretical and methodological, trying to suggest possible ways to *quantify* the bi-univocal and inter-dependent relationships between environment, social behavior, and social organization regarding survival in the past.

The *cause* of survival at a particular moment and place is then a *complex network of causal factors*. Here we follow Judea Pearl definition of *causality* as an answer to a *why*-question (Pearl, 2000; Pearl & Mackenzie, 2018): *causal factors* are those that their occurrence increases the probability of finding material evidence of survival -and decreases the probability of evidence of abandonment and starvation. We assume they are “complex” causal factors because they interact in multiple ways and follow local rules, leading to nonlinearity, randomness, collective dynamics, hierarchy, and emergence.

In this study, we will focus on exploring the impact of environmental change and variation on social activities related to the economy that agropastoral groups might have adopted in the face of scarcity. We intend to discuss the particular dependencies –probabilistic relationships and hence, causal relevance- between particular *landscape local conditions,* features of social life related to the *social organization* (type of settlement, number of inhabitants, observed inequalities), the general kind of *subsistence strategy* (foraging and agropastoral resources consumption), and the particular decisions taken to prevent the risk of scarcity (*social decisions*).

The discussion in this paper is based on results from a previous study (Palacios et al., 2022), in which we analyzed 173 ethnological examples for statistical dependencies between landscape characteristics, socioeconomic strategies, and social decisions. Case studies were described from two open-access repositories: D-PLACE (Kirby et al., 2016) and The Human Relations Area Files (eHRAF) (Moore, 1965). The first one provided most of the information, and eHRAF was used to confirm the data. This previous study focused on the method and primary results. In this paper, we increase the scope of results within a more developed theoretical framework. Another innovation in this paper is to apply the resulting statistical model to predict the most probable location of archaeological evidence related to survival when we know the general characteristics of the human groups implied (global subsistence strategy). In other words, we are looking for the kind of locational decisions that took ancient (prehistoric) agropastoral groups when they decided to reduce risks of starvation in the face of scarcity. Instead of traditional site location predictive models, which only take into account the landscape characteristics environment (e.g., elevation, mean temperature, soil net productivity; *inter alia*), we introduce social factors that may affect the decision to place the settlement on a particular area or elsewhere.

Results of our previous study suggest that agropastoral communities lived in more diverse locations and individual factors constrained fewer particular forms of living and working. For instance, the model that we have built suggests that animal husbandry was not limited to a singular niche as herders could move their flocks seasonally. Beyond landscape influence, our results also indicate that social decisions were also influenced by the kind of dominant subsistence strategy and the way the community was organized.

The impact of risk-mitigation strategies on survival expectations of early farming communities has been explored by many authors (e.g., Winterhalder, 1997; Winterhalder & Smith, 2000; Nettle, 2009; Ahedo et al., 2019, 2021; Dressler et al., 2019; Honeychurch & Makarewicz, 2016). Nevertheless, research has typically explored in detail only one strategy. While these applications have been provided significant contributions on our current knowledge of social decisions in prehistoric societies, there is at present no discussion about the probability of alternative survival strategies and how social decisions were mediated by social organization itself.

2. Materials and Methods

Instead of classical structural equation modelling, and following Pearl (Pearl, 2000; Glymour et al., 2016), we have calculated the network of probabilistic dependencies among intervening factors and attributes, with the assumption that the higher the probability from input to output, the higher the causal relevance from cause to effect. We have employed Bayesian Networks (BN) (Franzese et al., 2012; Koller & Friedman, 2009; Moschovakis, 2001) to model probabilistic dependencies. BN is a supervised machine-learning algorithm that learns statistically and illustrates the conditional dependencies of variables using a directed acyclic graph (DAG). Nodes represent variables and their links represent conditional dependency.

BN is a method that has gained importance in the last years in ecology and socio-natural systems modelling. One of the most common uses of this method is to forecast and predict the evolution of socio-ecological systems in the face of change or resources scarcity (e.g., Ropero et al., 2021; Keshtkar et al., 2013; Barton et al., 2012; Sperotto et al., 2017; Léger et al., 2006; Merritt et al., 2016; Pan et al., 2019; Khan et al., 2018). However, the application of BN in archaeology is still rare. Whilst Bayesian statistics has gained popularity in the last years, especially for its application on radiocarbon dating (e.g., Otárola-Castillo et al., 2023; Crema, 2022; Pardo-Gordó et al., 2022) but also in other fields (Otárola-Castillo et al., 2022; O'Shea, 2004; Hitchings, 2022; Krzyzanska et al., 2022), the application of BN for modelling SES is still uncommon. Some of the few research studies exploring the dynamics of ancient and prehistoric populations using BN include Terrell et al. 2023, Wang and Marwick 2021, and White et al. 2017.

We have built a BN model to analyze the mutual dependencies of social decisions with environmental and socioeconomic variables. Environmental features are defined as independent qualitative variables (input), whereas the outputs are alternative subsistence strategies, the kind of social organization and the particular social decisions taken to cope with scarcity (**Table 1**).

INDEPENDENT VARIABLES	**DEPENDENT VARIABLES**		
Environment	**Subsistence strategies**	**Social Organization**	**Social decisions**
Landscape Distance to coast Elevation Slope Annual mean temperature CV Annual temperature Monthly mean Precipitation CV Annual precipitation Monthly primary net soil productivity CV Primary net soil productivity	Agriculture Animal husbandry Hunting Gathering Fishing	Community size Settlement types Community organization Household organization	None Resource diversification Crop specialization Foraging intensification Storage Transhumance Temporal / Permanent migration Exchange in-/out-settlement Reciprocity for prestige

Table 1. Summary of the variables analyzed in the BN model. The model included independent variables (those related with the environmental and topographical characteristics) and dependent variables (social decisions and socioeconomic organization) (Palacios et al., 2022).

The list of alternative activities related to the economy that agropastoral groups may have adopted when they experience scarcity (*social decisions* in our nomenclature here and in Palacios et al., 2022), is based on ethnographic literature (Ravera et al., 2011; Ifejika Speranza, 2010; Belay et al., 2005; Homewood et al., 2019; Kardulias, 2015).

Dependencies between all those variables have been computationally induced from a 173 ethnographical cases database (details in Palacios et al., 2022). Instead of a theory-based approach in which the direction of edges is imposed by the expert, and conditional probabilities come from prior knowledge, we have used an inductive approach for the Bayesian learning of structure (edges and dependencies) and parameters (conditional probabilities). When possible, we used Augmented Naïve Bayesian learning (also known as 'Tree Augmented Naïve Bayes') (De Campos et al., 2016; Keogh & Pazzani, 2002) which is an extension of the classical Naïve Bayes algorithm (Koller & Friedman, 2009). Unlike the Naïve Bayes, the Augmented allows dependencies between the features and, therefore, may capture the system more realistically (**Figure 1**). However, when the statistical variation of the ethnographic database was not enough given the scarcity of appropriated cases, we used the Naïve Bayes, which is limited to the estimation of feature likelihoods or probability of observing that particular feature given the class label.

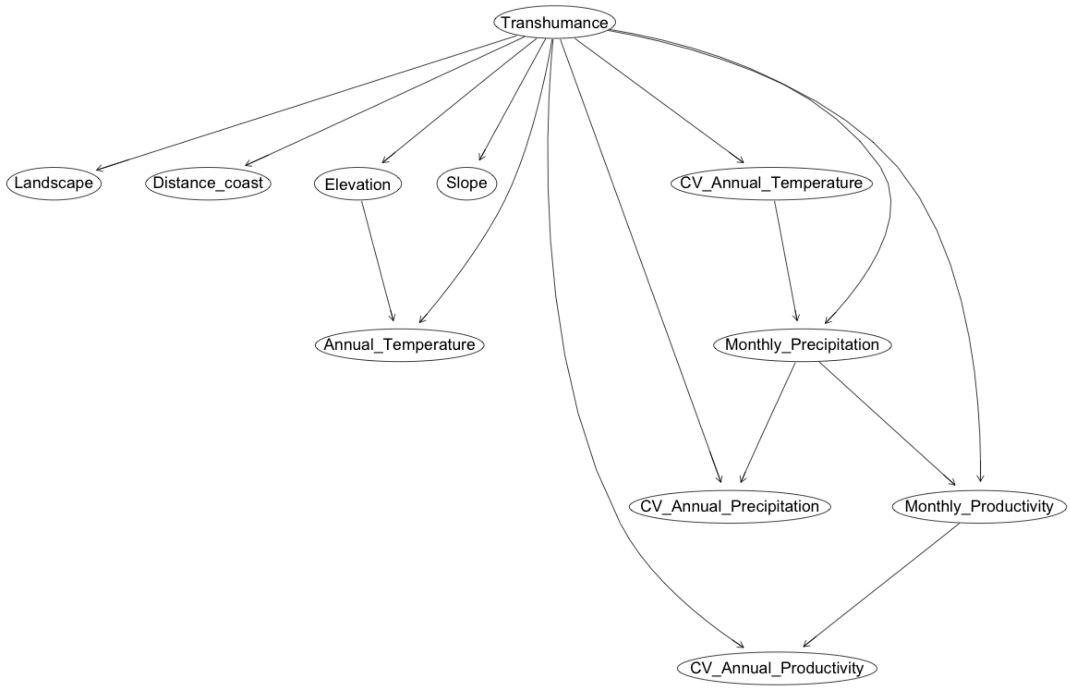

Figure 1. Augmented Naïve Bayes model representing the relationship between the social decision of transhumance and environmental variables. Most environmental variables are highly related among them such as net soil productivity, temperature, and precipitation. Conversely, landscape, and distance to coast seem to be less associated with the rest of variables although still significant for the practice of transhumance. In Palacios et al., 2022 there are other similar graphs representing the dependence network between the rest of environmental and social variables.

Different scenarios were compared, each one based on a different variable root, and determining feature dependencies with the goal to capture all the potential relationships among variables. For each pair of features (excluding the class node), the algorithm calculates the mutual information between them which is the statistical dependence between these variables. The structure of the dependencies network is then built finding the maximum-weight spanning tree, where the weights are based on the calculated mutual information values. The class node is connected to all other nodes in the network. Once the structure is determined, the procedure estimates the conditional probability distributions for each node given its parents based on the training data. Given a new instance with feature values, perform inference in the Bayesian network using Bayes' theorem to calculate the posterior probabilities of the class label. Finally, the different models corresponding to multiple possible scenarios were captured statistically.

3. Results

In the explored ethnographical cases, the percentage of farming communities not adopting any particular activity in the face of scarcity was higher than the communities that did it. That means that in conditions of agropastoral survival strategies it has been hardly frequent to make mid/long term expectations on survival and adopt strategies to minimize risks.

However, when some economic activity was implemented to reduce the risk of starvation, the social decision was constrained by different environmental *and* social factors. In our analysis, we have quantified the frequency a community adopted a particular activity in some specific environmental conditions. Our results show that some decisions are related to the local environmental circumstances (**SI Table 1**). In settlements located high, human groups tend to specialize their diet either in foraging or domestic resources (in addition to transhumance which would be expectable), whereas when they are in lowland, storage is preferred. Also, foraging intensification are more frequent in communities that have settled in areas with high net productivity soils. Soil productivity has not any relevant impact on the frequency of social decisions towards adopting crop specialization to increase the chances of survival. The adoption of any risk-minimizing economic activities seems to be related with particular environmental conditions. For example, in locations near to water resources not any activity seems necessary, as it is the case in tundra landscapes.

We have not observed any trend to adopt certain strategies to increase the chances of survival, probably because the risk of starvation was lower than in other environmental conditions. In extremely arid landscapes (desert), the adoption of transhumance and temporal migration are much more common. In elevated locations there is a much higher probability of different types of risk-minimizing activities (e.g., transhumance, foraging intensification, exchange), or a combination of them, than in lower altitude regions. Other positive dependencies found in our ethnological database suggest that exchange within the local group is more probable when the mean soil net productivity is variable through the year, and the relevance of storage increments in settlements located in high altitude areas.

The most common strategy for risk-minimization is just expanding the production area, what makes ecological niches less restrictive, and it reduces the constrains imposed by local environmental factors. However, such a way of minimizing risks implies maximizing labor efforts. What may seem paradoxical is that this maximization is not necessarily reduced by increasing technological efficiency or by adopting more complex but more efficient forms of social organization. Our results suggest that so-called "simple farming societies" assume the increase of costs without considering particular forms of increased efficiency. Technological development and social organization complexity were not directly caused by the threats to survival that the environment may have caused.

The scenario seems to be different for societies that depended on foraged resources, even partially. Our results show that they are influenced by the ecological conditions of settlement locations.

In those cases, risk-mitigation strategies are not only strongly associated with the ecological characteristics of the local niches in which the acquisition of resources was performed, which is expectable.

4. Discussion

We conclude that farming subsistence strategies have been performed in a wide range of different landscapes since its beginnings in prehistory, and therefore there is no direct linear dependency between environmental features at certain landscape areas and social economic decisions but there are some landscapes that increase the probability of some social decisions. This preliminary conclusion seems at odds with traditional adaptive theories that explained social decisions regarding subsistence as determined by environmental factors (Adger et al., 2009; Wolf, 2011). Most studies about the relationship nature-society assume the independence of environmental factors among them. We have tested this hypothesis and checked the increase in predictability when correlations between environmental factors are considered. Temperature average and temperature variation are correlated in most cases, in the same way as in the case of precipitation and soil productivity. Settlement elevation and slope are correlated in many cases.

Our research explains the way that environment *constrains* social behavior, but do not determine it. In our model, the comparatively high impact of environmental conditions on the relative predominance of hunting and gathering contrasts with the low relative importance of most landscape factors on the predominance of agropastoral strategies, as reflected in the conditional probabilities calculated between both factors. In this case the impact of environment seems to have had a less conspicuous role. In our results, animal husbandry is only associated with monthly mean precipitation around the settlement area. This situation can be associated with the fact that small-scale communities practicing herding may practice seasonal vertical mobility to maximize herd production and survivorship in communities with mixed economies.

Barceló and Del Castillo (2020) have studied risk-minimizing activities in simulated hunter-gathering societies and show how increasing mobility or adopting more efficient technology is not necessarily a way of reducing the likelihood of economic failure (starvation). They show that the number of resources is as relevant as the difficulty of acquiring those resources and the difficulty of their transformation into subsistence. This is related with our result that societies practicing different forms of foraging are more dependent on the local landscape circumstances.

What seems more important is the strength of labor productivity over the absolute abundance of some resource. In our results, soil natural productivity has only an impact on hunting and gathering. It contradicts traditional hypotheses suggesting that a prior high soil productivity is paramount for farming.

Therefore, we can expect farming be practiced even where soils may have less productivity. The key point is labor productivity and technological efficiency, more than original soil productivity. This result demonstrates the importance of human agency and intentionality on modifying the environment even when more suitable location -in this case, more productive soils- would have been available. This result can be connected with J. Weisdorf (2005), based on prior proposals developed by Sauer (1952), Braidwood and Howe (1960), Rindos (1984), has compared the nonlinear relationship between labor productivity and the amount of labor force in two different scenarios, one based on foraging strategies, and one based of simple farming (Fig. 2). It can be observed how the marginal products (productivity) increments when agriculture is practiced with higher intensity, that is, when technology increases efficiency.

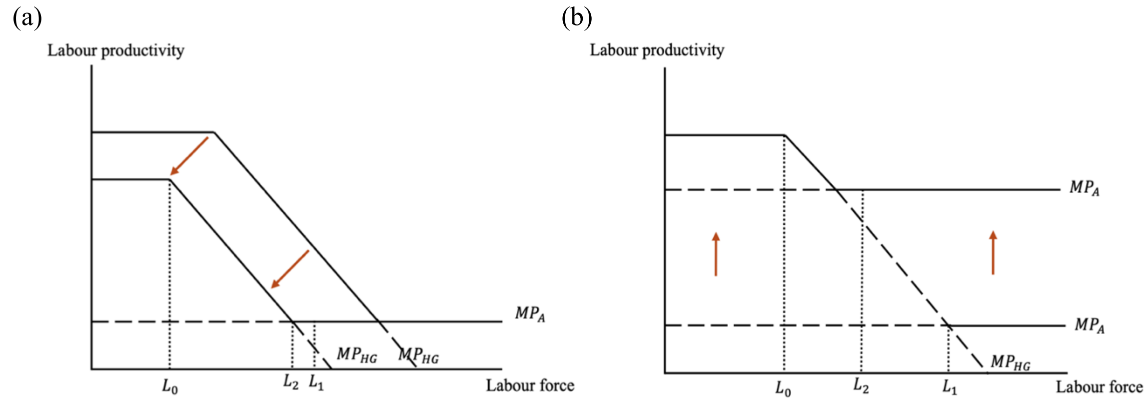

Figure 2. Comparison of two different subsistence models. (a) Communities prefer hunting and gathering resources and, (b) they prefer agriculture. L: labor force and MP: marginal product. Adapted from Weisdorf, 2005.

In this regard, it is interesting that in our model, the quantity of labor force (community size) constrains the social organization (Type of settlement) when predominant activity is agriculture, occasionally reinforced by gathering. Those results are obvious if we consider that the higher the number of people in the community, the more diverse will be its structure and organization, and the greater its dependence to subsistence strategies that may generate greater volumes of subsistence. On the opposite, the lesser the size of the human group, the more efficient will be generalized gathering activities.

Going deeper to early farming, our model questions the traditional optimization assumption of agropastoralism. This approach was applied to study agropastoral groups in Rindos (1984), who suggested that domesticated resources increased because they were available in the environment and people started to prefer them over foraging resources. A central point of his model was the influence of ecological variables to modify preferences and socioeconomic practices (**1**):

$$\mu_t = \frac{\mu_0}{1-\mu_0}\, e^{\lambda t} \left(1 + \frac{\mu_0}{1-\mu_0} e^{\lambda t}\right)^{-1} \qquad (\mathbf{1})$$

Where μ_0 is the contribution of agropastoral resources to the diet in a specific time considering the relative increment of their availability ($e^{\lambda t}$) compared to a previous time interval. The model also considers the preferences of people implying that the reduction of foraging resources (ϕ) caused a variation of subsistence strategies, W_t, and the amount of agropastoral resources at a specific time (D_t) (**2**):

$$\mu_t = \frac{D_t}{W_t\,/\phi + D_t} \qquad (\mathbf{2})$$

The model allows predicting the impact of this preference on demographics by including the amount of population (*N*) and its index (*d*) – birth and death rate, the population equilibrium/ carrying capacity (N_{max}) and the relative contribution of a specific food in the total diet (**3**):

$$\frac{1}{N}\frac{dN}{dt} = d\,(\frac{N_{max} - N}{N_{max} + \frac{d}{c}\,N}) \qquad (\mathbf{3})$$

The main problem with this model is its oversimplification. The only driving forces considered for change were the availability of resources and people preferences. Our causal factors are not exactly the same used by Rindos, but our results suggest the independence between the quantity of labor dedicated to foraging and the quantity of labor invested in farming. We cannot simply conclude that there is a sudden shift from foraging strategies to farming, expressed in the investment of labor force in one or the other strategy. Our results are in accordance with archaeological data suggesting that this change did not take place in the same way and with the same intensity in all territories (e.g., Robb, 2013; Leppard, 2022). In our database there is a relevant number of communities practicing both strategies, and differential productivity of both do not seem to be contradictory. After all, many early farming groups, especially in prehistoric Western Mediterranean seem to have alternated both strategies for quite a long time (Barton et al., 2010; Lemmen et al., 2011; Pardo-Gordó et al., 2015; Pardo-Gordó & Bergin, 2021).

In any case, Rindos model was an early attempt to investigate nonlinear relationships between human agency and ecological variables constraining survival at a historically relevant transitional period (Cannon & Broughton, 2010). More recently, some scholars (e.g., Spengler, 2021; Baedke et al., 2020; Neto & Albuquerque, 2018; Smith, 2011) have suggested enhancements to this simple model, but the underlying assumption that human agents intend to obtain the maximum benefit (calories) with the minimum costs (energy spent locating and handling the food) is something that our results do not support.

A recent variation of Rindos model including the importance of human agency in form of labor is developed by Chu and Xu (2022) in form of a Malthusian model (based on Locay, 1989; Baker, 2008). The model considers that all agents *N* are the same and each of them has *l* units of labor, which can be allocated to hunting-gathering (l_H) or farming (l_F) in a fixed amount of land *Z*. In case of farming, the fixed ratio of land given to farming labor is ρ, measured as $z = pl_F$. Each economic activity has a level of productivity (θ for hunting-gathering and φ for farming) and intensity (γ for hunting-gathering and α for farming). Then, the authors introduce the amount h of hunting-gathering food production units receiving the agent contribution l_H (**4**):

$$h = \frac{l_H}{l_H N}\theta(\bar{l}_H N)^{\gamma}(Z_H)^{1-\gamma} \qquad \textbf{(4)}$$

And the number of units of farming production *f* for an agent that contributes l_F (**5**):

$$f = \varphi(l_F)^{\alpha}(z^{1-\alpha}) \qquad \textbf{(5)}$$

Chu and Xu (2022) model the agent's decision to invest its labor on producing hunting-gathering or farming resources to maximize food production *x* given by (**6**):

$$x = h + f = \frac{l_H}{l_H N}^{\gamma}(Z_H)^{1-\gamma} + \varphi(l_F)^{\alpha}(Z^{1-\alpha}) = (l - l_F) \qquad \textbf{(6)}$$

A condition for a farming system is that most of the labor is destined to produce agricultural resources (**7**):

$$x = f = \varphi l^{\alpha}(\frac{Z}{N})^{1-\alpha} \qquad \textbf{(7)}$$

Thus, during the gradual transition from hunting-gathering to agriculture, the per capita output of food production is given by (**8**):

$$x = h + f = (l - l_F)\theta(\frac{Z_H}{l_H N})^{1-\gamma} + \varphi\rho^{1-\alpha}l \qquad \textbf{(8)}$$

Following this formula, the level of farming productivity increments as more labor is allocated to the production of this resources. Our results give support to this hypothesis. According to this model, if the population fails to reach the agricultural threshold, it will remain as hunter and gatherers. In this case, Chu and Xu conclude that a high agricultural productivity and high level of labor supply would have been paramount for the long-term survival of agropastoral groups. Again, this is an assertion that our investigation supports.

The relationship between diet, landscape and labor force is not linear and, as our results suggest, when considering other social factors as exchange (Winterhalder, 1997), migration (Winterhalder & Smith, 2000), or availability of labor force (Herzog & Goodale, 2019; Bettinger, 2009), predictability diminishes, indicating that the causal model should be more complex and even "complicated" (higher number of intervening factors).

Other models, like Bettinger (2009), also consider the causal relevance of labor productivity on economic rational decisions. Beyond the traditional focus on energy obtained and time spent for obtaining that energy, we should consider cooperation, activities sharing between different agents, as a way of minimizing the risks of diminishing returns. Our results go in that direction showing how alternate subsistence strategies have effects on the likelihood of survival.

5. Settlement Prediction Modelling

Our results highlight the apparent randomness for social decisions. Rather than concluding the lack of pattern or predictability in human behavior, randomness should be understood as the occurrence of events consequence of countless independent factors, equally probable, have, individually, little impact on the final outcome (Ayton et al., 1989; Horne, 2019; Landsman, 2020). If the probability distribution can be calculated, as we have done using an exhaustive database of ethnoarchaeological case studies, the frequency of different outcomes over repeated scenarios is predictable.

This is a particularly significant result because there is a long-standing tradition in archaeological settlement prediction studies of placing considerable importance on the natural setting to predict the placement of farming areas. The underlying assumption is that by modelling the most suitable landscape for productive economic strategies, the most probable settlement and occupation locations can be predicted. However, we have insisted in this paper on the low reliability of traditional hypothesis suggesting direct and linear landscape determinism. Our results go in the same direction as other studies (Vidal-Cordasco & Nuevo-López, 2021), emphasizing the lack of direct and linear correlation between farming and the ecological characteristics of the settled area. For instance, early Neolithic communities in Iberian Peninsula had far wider ecologically diverse niches than Mesolithic populations practicing hunting and gathering, much more adapted to local resources. When adopting agriculture and husbandry, the production area expanded, more ecological and landscape diversity entered into the catchment area, and the relevance of local features diminished.

It is important to distinguish *analytical predictability* from rational optimization. The more frequent a particular social decision in some determinate circumstances, the more probable is this behavior, and hence the easier to predict when the precise circumstances are repeated. Instead of mere frequency accounts of the number of times a settlement with archaeological evidence of farming has been found coincident with some environmental or ecological features, we should take into account existing dependencies among environmental and social factors, because the accuracy of social behavior predictions critically diminishes when there are non-linear relationships between predictive factors.

Other researchers have pointed out this question (e.g., Vidal-Cordasco & Nuevo-López, 2021; Ahedo et al., 2021), the traditional assumption that early Neolithic communities occupied different niches than late Mesolithic groups is difficult to sustain.

We have begun to work on an innovative site settlement predictive model that takes into account the dependency network between environmental and social factors extracted from our ethnoarchaeological data set (Palacios et al., 2022). The goal is to predict the location of early farming archaeological sites (Neolithic) in the Northeastern Iberian Peninsula. A database of known archaeological sites from the Iberian Peninsula is used to recalculate Bayesian network parameters. These new data suggest that early agropastoral groups settled in the Iberian Peninsula from c. 7,7-7,5 ka cal. BP (Bernabeu Aubán et al., 2003, 2009; Gabriele et al., 2019; Martínez-Grau et al., 2020; García-Martínez de Lagrán, 2018; Oms et al., 2017) in a wide range of different niches, types of settlements, and consumed different sort of resources. They likely worked the land through a small-scale intensive mixed farming system (Antolín et al., 2015; Antolín & Jacomet, 2015), as found in other Neolithic European contexts (e.g., Antolín et al., 2014; Pérez-Jordà & Peña-Chocarro, 2013; Bogaard & Jones, 2007; Bogaard, 2004). Present archaeobotanical data suggest that preferences for plant species varied depending on the region. For instance, in the Meseta with colder environments, the consumption of einkorn and emmer was more stable rather than in the northeastern area (Peña-Chocarro et al., 2018: 376). The preferences for particular domesticated animals seem to vary also geographically, suggesting how the local landscape may have constrained social decisions. Intra-regional differences are observed concerning the animals preferred. For instance, in the north-eastern region preferences are observed: some sites consumed more bovids (e.g., Carrer de Reina Amàlia, 31-33) while others ovicaprine animals were favored (e.g., Cova del Frare) (Saña et al., 2015; Saña & Navarrete, 2016).

The variation in settlements type and internal organization is very high: hamlets, caves, rock-shelters and open-air with upraised structures are found. Despite caves have traditionally been interpreted as secondary establishments related to main open-air settlements (Bosch, 1994), some of them were occupied permanently and had different uses. For example, Cova Colomera was used as a pen for sheep and goats but also used as settlements (Oms et al., 2015). Some were also used as base camps (for example, Cova del Frare, Cova del Toll, Cova de la Font Major) (Cabrià et al., 2014). Due to taphonomy and anthropic processes, settlements located in rock-shelters and caves tend to be better preserved than open-air sites. In this latter case, buildings are usually recovered from stick holes (e.g., Balma d'Auferí, Abric de Pontet or Barranc d'en Fabra sites), or storage pits (e.g., Guixeres de Vilobí, Mas d'en Boixos, La Serreta, la Vinya d'en Pau, Cinc Ponts, Els Pujols). Only in very few cases it has been possible to measure the size of occupation. In the north-eastern, settlements such as Plansallosa (Alcalde et al., 1991; Bosch et al., 1998) or La Draga (Andreaki et al., 2020) had a surface of c. 1000-2000 m2, with ellipsoidal and rectangular huts (approximate 8-12 meters in length and 4-5 in width), surrounded by fences to keep animals and cultivation fields. There were probably smaller occupations and size likely change through different events. For instance, in La Draga it is recorded an ongoing change and rebuilding of structures.

Hunting activities were generally reduced to a relative frequency of 30% in early farming sites (Tarifa-Mateo et al., 2023; Saña, 2013; Saña et al., 2020) although exceptions are observed in the northern and southern coast where wild animals represented between the 70 and 99% of faunal remains (Altuna, 1980; Mariezkurrena & Altuna, 1995; Saña, 2013). This fact gives more support to the hypothesis that there is not an abrupt differentiation between both subsistence strategies. Another evidence of the continuity of hunting practices are the presence of projectiles, arches, and arrowheads in settlements.

Foraging activities were also relevant in their diet, and their importance also varied depending on landscape and environmental characteristics. For example, in the northern coast, settlements specialized on the consumption of wild resources such as Herriko Barra were located near other settlements with a diversified diet like Arenaza (Pérez Díaz & Peña-Chocarro, 2015), or in the south also wild animals were consumed with higher intensity than domestic animals (Saña, 2013). That does not imply the necessary opposition between two alternative subsistence strategies, but it suggests a mosaic-like system with different intensities and preferences, in which social decision was constrained but not determined by the environmental and ecological characteristics of different landscapes. Gathering continued playing a major role in the diet of agropastoral groups. A wide range of different wild species have been recovered including hazelnut, acorn, rose, blackberry, red elderberry, grape, wild cherry, juniper, bog pine. Leaves, aromatic and medicinal plants were also probably consumed (Antolín & Saña, 2022). Besides their nutritional value, most wild plants were used as fuel (i.e., acorns, pine, fungi) or to manufacture tools (i.e., red elderberry, *taxus baccata*) (Piqué et al., 2015, 2020) and some for their medicinal value (Antolín & Jacomet, 2015: 23).

Remains of fishing activities, although very scarce, cannot be denied. Recently, the question of whether fishing played a relevant role in the Neolithic package has been addressed and it seems that fish and shellfish consumption was reduced over this period (Salazar-García et al., 2017, 2018) and it only had a regional and local continuity (Mazzucco & Gibaja, 2018; Edo et al., 2022) but not throughout the peninsula (Blanco-Lapaz & Vergès, 2016).

When introducing data from preceding archaeological sites (Mesolithic), characteristic of hunter-gatherers mobile groups, we must face up to the fact that both subsistence strategies coincided in Iberian Peninsula for more than 2000 years. Although subsistence strategies were different and even not all farming populations survived in the same way nor distributed labor force among different activities in the same way, there is no clear-cut differentiation in the landscape characteristics of their settlement location (Vidal-Cordasco & Nuevo-López, 2021). This result poses serious problems when trying to predict the location of Neolithic sites from landscape features alone. This prediction is even more difficult given the archaeological evidence of population movements between contemporary sites, associated with transhumance and pastoral activities (Fernández-Giménez & Ritten, 2020; Antolín et al., 2018). Archaeological record provides evidence for the practice of at least short-distance vertical movements, from settlements located in the lowland to nearby pastures at higher altitudes (Gassiot et al., 2012; García-Ruiz et al., 2020; Rojo-Guerra et al., 2013, 2014; Tornero et al., 2016). Possible, rock shelters and caves could have played a relevant role as shepherd huts, enclosures, or shelters in case of unfavorable weather conditions (Palet et al., 2014).

However, that does not imply that it is not possible to obtain meaningful information. Instead of predicting the location of settlements, the type of social decisions seems to be correlated with the landscape features. For example, we could use the same variables that we have employed in the ethnographical model but adjusting the social decisions to the archaeological record (**Table 2**).

Attributes	Description	Archaeological visibility
None	No action is taken, human group continues producing the same resources with the same intensity even in face of scarcity. This behavior has been defined as ‘supply-induced scarcity’ (Menghitsu et al., 2020; Belay et al., 2005).	None.
Resource Diversification	Introduction of new foodstuffs	New foodstuffs are present in one event compared to the previous one
Crop Specialization	Abandon the production of other resources to specialize in one staple crop to obtain surplus	Major presence of one type of crop
Foraging Resources Intensification	Cease agropastoral practiced intensifying foraging economy	Only foraging resources are found
Storage	Consumption of surplus produced in previous years	Presence of storage units (pits, baskets, large vessels, concentration of food remains, communal superstructures) (Prats et al., 2020)
Transhumance	Seasonal movement of livestock	Presence of settlements occupied only seasonally, shepherd huts, pen deposits in caves (Gassiot et al., 2012; Garcia-Ruiz et al., 2020; Rojo-Guerra et al., 2013, 2014; Tornero et al., 2016)
Temporal Migration	Seasonal or temporary migration of the entire domestic unit to another place (i.e., winter on the coast and summer in the mountain)	Household abandonment, variation of occupation during different events of the settlement
Permanent Migration	Permanent abandonment of the settlements	Abandonment of the entire settlement during a settlement event
Exchange Out-settlement	Resources exchange with other settlements than the one inhabiting	Presence of foreign materials (e.g., obsidian, ceramics) or food resources (fish and mollusks in settlements away from the coast)
Exchange In-settlement	Resources exchange between domestic units of the same settlement	Difficult to identify. Ideally, different concentration of specific type of resources and/or materials found in households
Reciprocity for Prestige	Give resources to other people to strengthen the relationships with other domestic units and establish social networks	Speculative in most times. Communal superstructures, monumental buildings, foreign materials and artefacts (Nakassis et al., 2016; Harris, 2006; Kohler et al., 2000)

Table 2. Summary of the social decisions that agropastoral communities could have adopted to cope with scarcity and their archaeological visibility. They have been defined from ethnoarchaeological literature (Ravera et al., 2011; Ifejika Speranza, 2010; Belay et al., 2005; Homewood et al., 2019; Kardulias, 2015). Developed by the authors.

Many of the variables and factors used to describe our ethno-archaeological and ethno-historical cases are not archaeologically observable. To fully use this approach to understand survival in prehistory we need to make assumptions. They come from the data-based model, but they are more "valid" than really "true". This is the basis of our expert Bayesian model. Causal dependencies are built in form of chains following Causal Markov assumption. They are based, however, on expert knowledge, not on empirical data. Given the nature of archaeological information, data-based models cannot be complete without adding factors and links deduced from theory. These models can be tested at the end, using archaeological data. Survival in prehistory is testable in terms of the presence and temporal continuity of settlement.

6. Conclusions

In this research study, we have observed that environment does not always influence the choice of a particular subsistence strategy or a determined form of social organization. The relationship between social decision and environment is far more complex than a simple direct causal link. We have built a probabilistic model reflecting the assumed non-linearity of multiple dependency relationships between social factors and landscape features on risk-minimizing social decisions. We have proved that individual factors have a low or very low causal strength. To understand how people survived in Prehistory we should focus on the multiplicity of factors, their non-independence, and non-linearity, taking into account that any of the intervening factors is enough for understanding the social output.

To build the model, we have used ethnoarchaeological data. We have used this kind of data to establish and measure what behaviors are more 'probable' in different contexts (David & Kramer, 2001; Politis, 2014) but not to establish analogies with the archaeological record. We cannot aim to infer the knowledge obtained by investigating modern human groups to explain how people lived in the Neolithic. This is an inherent gap. Therefore, in this study we have used ethnoarchaeology to generate models and hypotheses to explore through the archaeological record, but not for validation.

Early agropastoral groups had a mixed economy, consuming foraging resources in addition to plant and domestic animals. Also, their diet was not static, resources were consumed in different intensities depending on the settlement, the region, but also probably the period. However, this dynamism is difficult to identify in the archaeological record. As previously mentioned, some types of plants and animals were consumed with higher intensity, denoting a specialization of some crops and intensification of foraging resources. The number of studies arguing the mobility of early agropastoral groups especially in mountain regions has also exponentially increased in the last years. Despite it is still do not know exactly the nature of mobility activities, it is evidenced that they moved into other locations. Movement of people, movement of resources, interactions among people inter- and intra-settlement are very difficult to identify in the archaeological record and they probably played a crucial role in the long-term survival of early agropastoral groups.

Concerning the potential limitations of BN, they are the same for all supervised machine learning methods: they are restricted to labelled data and that implies a trade between 'archaeologically meaningful' and 'computationally efficient', since the number of categories per variable need to be few for reducing the computational power, we are simplifying the available data. Additionally, all values should be equally distributed but that is very difficult. Values are represented in the dataset and, if there are few cases with a certain value, its prediction will have lower accuracy rather than other values more represented.

Obviously, causal models cannot be reduced only to probabilities. Therefore, we have introduced our contribution with a discussion on equation models, and how to enhance traditional foraging models, more or less based on Classical prey-predator Lotka-Volterra equations, with the effects of quantity of labor, effectiveness of technology, and the needs derived from social reproduction. After all, survival is not just about "eating and drinking", but about the processes to make tools, define social ties and social reproduction implying all social agents.

We should look for:

a) the particular sequence of events explaining how those people found enough resources at that place and time,
b) how they exploited those resources and transformed into subsistence with available labor force and technology,
c) how they interacted with competitors (animal or human) for the same resources,
d) the reaction of the environment to their extraction work, the capability of the same environment to reproduce naturally resources,
e) how the human group biologically and socially reproduced to continue their existence at the same place,
f) how they altered the place of work, the place of residence, their technology, the resources they exploited, their interaction network to continue their existence (and that of their descendants) at the same place or at a neighboring place.

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Chapter 4

Conclusions

4.1. Research Overview

In this thesis, we have explored one of the most debated topics in prehistory: the relationship of agropastoral groups with their environment, and how the availability and limitations of the landscape transformed the ways people produced, consumed, and interacted. This relationship has been explored from multiple angles and methods and, in most cases, its equilibrium has been used as the *cause* of change, transformation, or disappearance of these groups. Environment, location, places, landscape are used interchangeably in this thesis as these concepts all come down to the same concept: independent variables not controlled by humans.

The methodological and theoretical frameworks of this thesis are explained in Chapter 1. Since the development of the Evolutionary Theory approach, scholars have stressed the idea that the environment may have determined the chances of survival. However, this hypothesis has been examined in the last decade as more importance is placed in human agency and behaviour for studying the actions in the past. In this line, the Niche Construction Theory emphasises the importance to consider agency as driving force for innovation and transformation of the landscape. Therefore, humans can survive even if they are located in precarious locations by modifying their behaviour in terms of social organization (e.g., labour force, exchange), economic activities (e.g., intensifying the consumption of certain foodstuffs or diversifying the production), and environment (e.g., deforestation).

We have followed the Niche Construction Theory as the theoretical framework to conceptualise early agropastoral groups. Our basis for modelling these systems was the Complex Systems Theory which argues that systems can be divided into inputs, outputs, and mechanisms. In this chapter, we have discussed the principal computational methods used in archaeology but especially for modelling socioecological systems and how models are built for this purpose. In this study, we have focused on Machine learning because when we started this research in 2019, we felt that the number of studies in archaeology applying this method was exponentially increasing but there was not any research done concerning its different algorithms, benefits, and limitations in archaeology. The only studies done up to that time discussed in a general way the advantages of the method but not a clear comparison of algorithms, guidelines for designing the models or software were provided. For this reason, the research study of Palacios (2023) was developed, aiming to fill the gap an characterise the application of machine learning in archaeology through a bibliometric study. Interestingly, the results obtained evidenced the initial perception that the number of studies applying machine learning were increasing, it was in 2019 when this increment started. It was also observed that the selection of machine learning algorithms did not consider the type of data for selecting the most suitable algorithm, but it was common to apply the exact same algorithm in all studies of the same field.

We have focused on one specific machine learning algorithm, the Bayesian networks, for four reasons: (i) it is a machine learning method and we wanted to explore its applicability to investigate this topic; (ii) Bayesian statistics have gained popularity in recent years and we wanted to explore whether they can be applied to model relationships between social variables; (iii) it is the only probabilistic supervised machine learning methodology and that means that it is a 'white-box', and a predictive model that provides graphical representations; (iv) Bayesian networks are uncommon in archaeology but have shown great potential in other fields for modelling uncertainty. Therefore, we wanted to explore whether this method is suitable in archaeology and, especially for studying farming communities.

In Chapter 2, we have presented the current status of the archaeological evidence used to model the transition from foraging to early agropastoral systems in the Mediterranean. This topic is probably one of the most explored and debated in archaeology and recent studies shed new light on the when, where, how, and possible 'whys' this transition took place. While the traditional discourse was built as a narrative of sequences that started from less complex groups towards more advanced social systems, current empirical evidence demonstrates that this transition was a long, dynamic, and arrhythmic process with general patterns and local variations.

To explore this, we have provided first the empirical evidence of the archaeological record and then how researchers have modelled this evidence for interpreting these changes. We wanted to discuss the different elements that researchers have previously considered, the inputs, outputs, and mechanisms to gain a general overview of what variables were relevant for explaining the development of agropastoralism and its expansion across the Mediterranean. The research study published as Barceló and Palacios (2023) discusses specifically how we can model people displacement in migration processes from the evidence of migration throughout the Mediterranean during the early Neolithic. Our preliminary Bayesian Network application aimed modelling migration and defining what variables we may consider. We combined this study with the results obtained in the previously developed agent-based model named NEOLSPREAD v.04.

Chapter 3 discusses the arrival of early agropastoral communities in the Iberian Peninsula, which has traditionally been interpreted as a crucial change in the landscape. Hence, agropastoral groups would have inhabited different ecological niches than foragers as they would have looked for optimal locations for farming (e.g., high soil productivity, low slope, etc.). Research conducted in the last years is proving this assumption wrong as it is evidencing that both foragers and agropastoral communities shared ecological niches. That makes sense since most forager settlements had continuity during the Neolithic period. That does not mean that all settlements were the same, but there is not a specifical landscape characteristics that allow us to define that it was unquestionably a Neolithic or Mesolithic settlement. We have observed differences in the foodstuff consumed among Neolithic settlements. There were some resources that were more consumed in some areas than others.

To quantify the influence of the environment in survival probabilities of agropastoral groups, we built a Bayesian networks model to measure the relationship among environment, social organisation, and socioeconomic strategies. With the ethnographical model, we identified patterns and preferences that are common in cross-cultural agropastoral societies. By comparing different groups, we knew what variables were more present and in what sort of landscapes. On the other hand, if we had only considered groups from the same region, it would have not been possible to identify cross-cultural patterns. It was enriching for obtaining an overview of different ways of agropastoral organisation in different regions, landscapes, and cultures in the world. The results obtained are significant for understanding how systems organise, what practices are more common in some landscapes rather than others, but not for extrapolating these results into the early Neolithic.

Our model is explained in two research studies, Palacios et al. (2022), and Palacios and Barceló (2023). Palacios et al. (2022) is focused on the methodological development of the model as it explains the preparation of data, and the different algorithms used for building the Bayesian Networks. Also, the relationships among landscape, social organisation, and socioeconomic strategies are explained in detail, concluding that the landscape is not a crucial factor for defining agropastoralism lifeways, since they can modify their production through organization. The starting point of Palacios and Barceló (2023) are the results obtained in this previous study and is centred on the role of social decisions to ensure the survival of agropastoral communities. We defined social decisions as those decisions that are made to cope with scarcity and ensure the survival of the community. The results evidence the importance of these activities as they allow communities to inhabit in a wide range of different ecological niches.

What is especially interesting about our model is the lack of correlation between variables that we thought to be clearly connected. Our results point out the importance of organising the work and the dynamism in this sort of society. The possibility of increasing the type of resources produced and exchanging them seasonally or temporally may be even more important than the location and environmental characteristics. That does not mean that it was not important, but it only highlights the capacity of people for transforming and shaping their landscape to meet their needs.

4.2. Results

We have partially achieved the objectives defined because we could not apply the model to a prehistoric dataset due to resource constraints. As already stated in the previous chapters, we used an ethnographical dataset because it was not possible to build the model from archaeological evidence of early agropastoral settlements due to several reasons associated with the data and knowledge limitations. Practices such as transhumance, exchange, crop intensification, or community size, are difficult to identify and measure in the archaeological record and it was already available in open access in ethnographical repositories. We decided that it was a good opportunity to use this data for building a first model and including all those variables that we considered that could have influenced the survival of agropastoral communities.

For an archaeological application, we would need a large dataset of prehistoric case studies (settlements). For every settlement, we would have recorded their landscape characteristics, the intensity in which every subsistence strategy is practised, the number of people living there, whether inhabitants exchanged their resources, if they migrated, what social decision they preferred, etc. It is not impossible to have such dataset, in fact, there is an increasing number of settlements that some of the variables of social decisions have been recorded. However, they are a minority. Such dataset is possible, but it needs further time and resources that the ones that were available for conducting this study.

Considering this, we proceed to answer the objectives specified in the Introduction chapter:

OBJECTIVE 1. Assess the suitability of Bayesian networks for modelling past socioecological systems

After constructing and applying a Bayesian Network model to explore the socioecological variables of agropastoral groups, we strongly believe that this methodology produces competent predictive models when multiple variables are considered. As other machine learning methods, it can be applied to explore the data, predict unknown evidence from the collected dataset, and to explain the interrelationship between multiple variables. In addition, Bayesian networks, produce graphs in which these relationships are represented, and each value of every node is measured and depicted in conditional probability tables. As a result, the interpretation of Bayesian networks is clear and unambiguous.

As previously mentioned, it is a method that predicts the trend, not the outliers. If it is aimed to explore a very specific case because it is different from what we observe in similar contexts, none of the ML algorithms would be suitable for that purpose. Another limitation of all Machine learning algorithms including Bayesian networks is the limitation on experimentation. It is not possible to experiment with values that are not included in the dataset. It is not possible to experiment with evidence that we do not have. This can represent a limitation when modelling past socioecological systems, since most of the times the goal is to understand the internal mechanisms of the system. With Bayesian networks and other machine learning methods, we cannot ask questions like: How much would have changed if people ate that food instead of the other? What if the settlement had been bigger? What labour organisation would have been the most efficient in that environment? To answer these questions, simulation models such as agent-based would be more suitable. Simulation models offer the possibility to experiment with different options that might have occurred in the past and formulate hypotheses about their possible outcomes.

We believe that in the future it would be interesting to combine agent-based modelling with Bayesian networks methodology. Bayesian networks to explore the data, identify patterns and predicting unknown cases, and agent-based modelling to experiment with the predictions to better understand their mechanisms. We consider that Bayesian networks can provide us with the probabilities of different events in multiple contexts which can provide us with a solid foundation for designing the simulation model. This combination of methods may be especially relevant to investigate past socioecological studies because most of the times the social aspects are not easily observed in the archaeological record and, therefore, *in silico* experimentation can provide insightful information.

It must be pointed out that to correctly assess the model suitability, we should construct the same model with other machine learning methodologies. It would be extremely interesting to investigate and identify what methods are more suitable for what kind of data, questions, programming capacities of the author, computational availability, etc. As seen in the research article Palacios 2023 (Chapter 1), it seems that every researcher applies the kind of method that knows or that it is popular in their specialisation without reasoning if it is the best suited and the most adequate one. It may be what we have done here. We chose a method, and we applied it in different studies and answered different questions. Was Bayesian networks the best method for studying ethnographical data, or the variables considered in Palacios et al., 2022 and Palacios and Barceló, 2023? Should we conduct the same study with different machine learning algorithms, statistical tests, and agent-based modelling? This study represents the first application for building a predictive model in archaeology with Bayesian Networks. By making the code available in open access, we hope that in the future it will be improved and applied to explore other contexts and its suitability will be better assessed and contrasted. Thus far, it seems that accurate predictive models can be built with Bayesian networks.

OBJECTIVE 2. Explore ways to quantify the likely impact of environmental features on prehistoric social behaviour, even when this impact may have been indirect

This objective has been partially accomplished. We were able to develop a model that disentangled the complexity of the relationships between the multiple variables embedding farming systems. We quantified the intrinsic non-linear and non-monotone nature of the relationship of ecology, social behaviour, and economic strategies. Results show that some landscape characteristics of the settlement areas may had influenced indirectly the type of subsistence strategy of the community. Also, we identified patterns, strategies that were more probable in some landscapes than others. Importantly, results demonstrate the importance of considering the type of organisation, settlement, and amount of people for predicting the most probable location of a farming settlement. Human groups can build different kinds of social organisation independently to the local characteristics of their landscape.

This study represents a starting point, it was conceived as an exploratory study for applying a particular method to investigate a specific system and we were able to quantify the probable impact of environmental features on prehistoric social behaviour, even when this impact may have been indirect. We were able to question traditional assumptions such as the crucial role of soil productivity for farming communities by demonstrating the diversity in mixed farming economies. Our study evidence that individual factors constrained fewer particular forms of living and working and, therefore, farming communities are not constrained by their location.

OBJECTIVE 3. Analyse the probability of social behaviour depending on different socio-natural contexts

We have been able to predict the most probable behaviour given different socio-natural contexts with our Bayesian Network model. That was possible because we built a model with a cross-cultural small-scale farming dataset that included all the possible combinations for the social domain of this kind of society. They were well-documented ethnographic cases existing in the literature. That represented a strength of this study as if we had limited to a particular area of study, we would have probably obtained fewer combinations and scenarios for experimenting with different socio-natural contexts. In the research paper of Palacios et al. 2022, we selected some particular socio-natural contexts for predicting the behaviour and obtained the most probable outcomes, but our model can now be reused by other researchers for predicting the contexts they are interested in.

From our point of view, what is a relevant contribution of this work is that underlines the importance of more than environmental variables for settlement prediction modelling. More variables, and not only landscape and environment, should be considered to understand how survival was possible thousands of years ago. For example, our model suggests that animal husbandry could not be limited to a singular niche, but herders could move their flocks seasonally and, therefore, adapt to many different environmental circumstances. Social decisions such as diversifying the resources produced, migration of people or the exchange of foodstuffs could have played a major role in managing and compensating the resource availability in the community.

OBJECTIVE 4. Investigate the social and economic dynamics of early agropastoral systems, how economic decisions may have affected chances of survival in the prehistoric past, and its consequences on the likelihood of finding enough archaeological evidence for a proper historical explanation

From the results obtained in Palacios et al. (2022) and Palacios and Barceló (2023), environmental features are not especially relevant in agropastoral communities. Other variables such as social decisions, the size of the community and the type of settlement are more associated with the kind of subsistence strategy of these communities. Therefore, from these results, we can hypothesise that the landscape would have not been crucial for these groups, and they would have been able to inhabit different niches. This is aligned with the archaeological evidence discussed in Chapter 3.

We were not able to measure the survival probability of these communities in different ecological niches because for that we would have needed a dataset with communities that survived and others that did not.

In the near future, we would like to build a Bayesian network model with landscape and socioeconomic variables of early agropastoral communities collected from the archaeological record. It would be interesting to add another variable specifying if the settlement had continuity after the Early Neolithic and, this way introducing the concept of survival. This way, we would like to explore patterns in settlement location and investigate whether it is associated with their socioeconomic practices. By doing so, we hope we will be able to assess the consequences of socioeconomic practices on the probability of settlement location.

4.3. Future Research Directions

This research aimed to investigate the relationship between the environment and the socioeconomic strategies of early farming communities. Thus far, we have only answered: **in what ecological conditions can agropastoral groups live?** We have not had time to apply the model to an archaeological dataset of early Neolithic settlements in the Iberian Peninsula and, for this reason, these results are still merely exploratory. Aligned with the archaeological evidence found in recent years, our results indicate that the environment was probably important for early agropastoral communities but not restrictive. Human agency, those actions that people carried out for transforming their surrounding socio-natural landscape was crucial. Unlike foraging communities, agropastoralists actively modified their location through mechanisms, either modifying the food produced and consumed (diversification of different resources, intensification of particular resources), their social relationships (exchange, labour force) or the environment (transhumance, migration). There was a nonlinear complex relationship between environment and settlement location.

These results call into question whether it would make sense then to construct a settlement prediction model for identifying agropastoral sites in the Iberian Peninsula, for example. In other words, if agropastoral sites could be located anywhere, we should not be able to find locations that have higher probabilities to have sites than others. This may sound discouraging, in the sense that it would be benefitial for archaeologists to design a model that points to very delimited locations and find Neolithic settlements with high accuracy. Nevertheless, we would like to stress that it is not. We are a small further step towards understanding how and why agropastoral groups ensured their long-term survival.

However, in this thesis we have not explored **if there are ecological conditions in which agropastoral groups could have never lived**. To do so, we would need to include case studies of random locations in which we know for sure that people never lived in our dataset. Environmental characteristics of every location would be detailed, but also other variables that could have potentially induced the absence of occupation. For example, it would be paramount to consider potential nearby settlements as the closer distance between settlements could have caused the territory in between to be unoccupied. Or the type of resources produced in those nearby settlements, as they could have used that space for cultivation or for herding and it has not been recorded archaeologically. Or the size of these settlements, since it may be necessary to have unoccupied territory near large settlements. Multiple variables would be recorded to predict the output ‘Survival =Yes/No’.

We have applied our study at a macro-level to identify patterns and trends, but it would be interesting to do at the micro-level as well to go further than Yes/No and investigate the how and why.

In the end, the principal contribution of this thesis is the development of the predictive model using a rather uncommon method in archaeology to explore a topic that has a long and controversial trajectory in prehistoric studies. However, this is only the starting point. This research concludes with more questions than answers. With the continuous innovation of methods, technologies, and settlements identification, we are confident that soon we will advance in our understanding of the why, how, where, and when agropastoral groups lived. We hope that further research focusing on the importance of what we have named here as 'social decisions' is conducted, going a step further the traditional linear relationship between landscape and subsistence strategies. We hope that we contributed, albeit to a small extent, in the discussion on the modelling of early agropastoral communities, helping to better understand them.

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(1) The Bayes Theorem.

(2) Node construction of bayesian networks (Koller & Friedman, 2009:51).

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(13) Fisher's equation for modelling demic diffusion, also known as the 'Wave of Advance' model (Ammerman & Cavalli-Sforza, 1984).

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Barceló, J.A. & Palacios, O. (2023). Computational simulation of prehistoric migrations. Western Mediterranean Early Neolithic case study. In V. Heyd & M. Ahola (Eds.), *Moving and Migrating in Prehistoric Europe*. London: Springer Routledge.

FIGURES

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FIGURES

Figure 1. Example of a BN to predict the type of settlement. Type of settlement (output, orange), agriculture and elevation (inputs, green).

Figure 2. Different general approaches for building Bayesian networks.

Figure 3. Some examples of binary associations found in the exploratory data analysis.

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Figure 6. Final Model B exploring the influence of the environment on subsistence strategies. In this scenario we predicted the correlations among the ecological characteristics (inputs) and the subsistence strategies (outputs).

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Figure 9. Model A-ANB exploring the relationship between social organisation and subsistence strategies. Dependence between social organisation (inputs, green) and subsistence strategies (outputs, orange). The relationship among input variables is the same for all the BNs produced for all the outputs examined.

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Table 2. Qualitative variables and their categorical values investigated in this research. It contains the 30 variables and their values. Ecological characteristics of settlement location and its catchment area are defined in nominal scales using integrative categories.
Table 3. Description and main characteristics of the three types of BNs.

Table 4. Final correlations of Model B exploring the influence of the environment on subsistence strategies. They correspond to the graph depicted in Fig 6 and only relationships statistically significant are included and their p-values are classified as follows: 0.05-0.01 = *; 0.01-0.001 = **; <0.001 = ***.

EQUATIONS

(1) Chain rule.

(2) Prediction example of a Bayesian Network.

SUPPORTING INFORMATION

S1 Table. Relevant variables to consider for building socio-ecological models according to prior studies.

S2 Table. Variables description. * We measured the coefficient of variation (CV) to explore the ratio of the standard deviation to the mean. We used the mean and variance, both specified in D-PLACE datavase [60]. ** Monographies of each society are specified in S2 Dataset and were extracted from eHRAF dataset [61]. *** Homesteads: isolated domestic unit; Camp: temporary location of huts or other structures where households live collectively during that period; Hamlet: formed by few several homesteads, it can be both dispersed and clustered; Village: like the hamlet, it is composed by several homesteads and it can also be both dispersed and clustered, but the village has more homesteads. It is the largest type of settlement in this classification.

S3 Table. Summary of the relevant relationships found. We followed [84] guidelines for interpreting relevant relationships of Cramer's V test: k = 2: Small (0.10–0.30), Medium (0.30–0.50), Large (>0.50); k = 3: Small (0.07–0.20), Medium (0.20–0.35), Large (>0.35); k = 4: Small (0.06–0.17), Medium (0.17–0.29), Large (>0.29).

S4 Table. Summary of the results of the statistical tests of hypotheses for the comparison of the predictive models, in each scenario. Only significant p-values are depicted in the table. Empty cells correspond to statistically non-significant probabilities. "Model 1 > Model 2" means that the alternative hypothesis (which is accepted if the p-value is < 0.05) is that the mean accuracy is greater for the Model 1 than for the Model 2. P-values are classified as follows: 0.05–0.01 = *; 0.01–0.001 = **; <0.001 = ***. In Model B, significant relationships among inputs are not represented (only among outputs) to avoid noise from variables that we do not predict and are expectable (i.e., the relationship among environmental characteristics).

S5 Table. Strength of the relationships of all scenarios. P-values are classified as follows: 0.1–0.05 = ·; 0.05–0.01 = *; 0.01–0.001 = **; <0.001 = ***.

S1 Dataset. Dataset employed in this study. A total of 174 case studies and 30 different variables are considered.

S2 Dataset. Consulted dataset for identifying the adaptive strategies of each case study.

S1 File. References of supporting information.

Palacios, O. & Barceló, J.A. (2023). Survival in prehistory: Disentangling the complexity of dependent relationships. *Journal of Anthropological Archaeology*.

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Figure 1. Augmented Naïve Bayes model representing the relationship between the social decision of transhumance and environmental variables. Most environmental variables are highly related among them such as net soil productivity, temperature, and precipitation. Conversely, landscape, and distance to coast seem to be less associated with the rest of variables although still significant for the practice of transhumance. In Palacios et al., 2022 there are other similar graphs representing the dependence network between the rest of environmental and social variables.

Figure 2. Comparison of two different subsistence models. (a) Communities prefer hunting and gathering resources and, (b) they prefer agriculture. L: labor force and MP: marginal product. Adapted from Weisdorf, 2005.

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Table 1. Summary of the variables analyzed in the BN model. The model included independent variables (those related with the environmental and topographical characteristics) and dependent variables (social decisions and socioeconomic organization) (Palacios et al., 2022).

Table 2. Summary of the social decisions that agropastoral communities could have adopted to cope with scarcity and their archaeological visibility. They have been defined from ethnoarchaeological literature (Ravera et al., 2011; Ifejika Speranza, 2010; Belay et al., 2005; Homewood et al., 2019; Kardulias, 2015). Developed by the authors.

EQUATIONS

(1) Rindos model for measuring the influence of ecological variables to modify preferences and socioeconomic practices (Rindos, 1984).

(2) Rindos equation considering preferences for agropastoral resources over foraging (Rindos, 1984).

(3) Rindos equation considering the carrying capacity of available resources (Rindos, 1984).

(4) Modification of Rindos model by introducing labour force (Chu & Xu, 2022).

(5) Model of the contribution farming production in agropastoral communities (Chu & Xu, 2022).

(6) Introduction of agent's decision to invest its labour on producing hunting-gathering of farming resources to maximise food production (Chu & Xu, 2022).

(7) Model the labour to produce agricultural resources (Chu & Xu, 2022).

(8) Modelling the gradual transition from hunting-gathering to agriculture (Chu & Xu, 2022).

SUPPLEMENTARY INFORMATION

SI Table 1. Relative distribution of social decisions depending on the environmental, social, and economic variables. All results are depicted in form of percentages.

Appendix

Palacios, O. (2023). Aplicación del aprendizaje automático en Arqueología: ¿Un cambio de paradigma?. *Vegueta. Anuario de la Facultad de Geografía e Historia, 23*(1), 147-186. https://doi.org/10.51349/veg.2023.1.06

Additional information from this research paper (Apéndice Tabla 1, Tabla 2 and Script 1) is published in open access in the publication https://doi.org/10.51349/veg.2023.1.06

Palacios, O., Barceló, J.A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. *Plos One*, *17*(10), e0276088. https://doi.org/10.1371/journal.pone.0276088

Additional supporting information is found in open access in the publication. Each document has its own identification number:

S1 Table https://doi.org/10.1371/journal.pone.0276088.s001

S2 Table https://doi.org/10.1371/journal.pone.0276088.s002

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S4 Table https://doi.org/10.1371/journal.pone.0276088.s004

S5 Table https://doi.org/10.1371/journal.pone.0276088.s005

S1 Dataset https://doi.org/10.1371/journal.pone.0276088.s006

S2 Dataset https://doi.org/10.1371/journal.pone.0276088.s007

S1 File https://doi.org/10.1371/journal.pone.0276088.s008

The code developed for designing the Bayesian networks can be downloaded in open access in GitHub, in the following links:
https://doi.org/10.1371/journal.pone.0276088
https://github.com/OlgaPal/Agropastoral-management.git

Palacios, O. & Barceló, J.A. (2023). Survival in prehistory: Disentangling the complexity of dependent relationships. ***Journal of Anthropological Archaeology.***

SI Table 1.

Variables	Values (%)	None (%)		Resource diversification (%)		Crop specialization (%)		Foraging Intensification (%)		Storage (%)		Transhumance (%)		Temporal Migration (%)		Permanent Migration (%)		Exchange Out-settlement (%)		Exchange In-settlement (%)		Reciprocity (%)	
		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Hunting	<25	66	50	66	66	64	90	65	72	67	58	67	58	66	65	67	57	67	64	66	66	67	59
	>=25	4	0	4	5	5	0	3	9	4	8	5	0	3	12	5	7	2	7	4	7	4	6
	None	29	50	30	29	31	10	32	18	29	33	29	42	31	23	29	36	30	29	30	28	30	35
Gathering	<25	40	50	43	43	55	90	43	41	43	42	44	33	44	38	44	29	40	46	41	48	43	41
	>=25	0	0	1	0	23	10	0	5	1	0	1	0	1	0	1	0	1	0	0	0	0	0
	None	60	50	56	57	21	0	57	54	56	58	56	67	55	62	55	70	59	53	58	52	56	59
Fishing	<25	48	0	45	48	47	40	44	59	45	58	50	8	49	35	47	43	48	45	49	38	46	47
	>=25	16	25	20	10	16	0	14	27	16	17	15	25	15	19	18	0	16	16	16	17	17	6
	None	35	75	32	40	36	40	41	14	37	25	33	67	35	42	35	50	37	36	36	38	35	47
Animal Husbandry	<25	57	50	58	57	55	90	59	50	55	83	60	66	61	42	56	71	57	57	60	48	59	47
	>=25	21	50	23	22	23	10	24	14	25	0	18	67	20	35	23	21	22	23	22	24	21	29
	None	20	0	20	20	21	0	16	36	20	17	21	0	19	23	21	7	20	20	17	28	19	24
Agriculture	<55	43	0	46	34	41	50	38	59	40	50	38	75	41	42	44	21	40	43	36	62	41	41
	>=55	54	80	51	60	55	50	59	36	56	50	59	17	57	46	53	71	57	52	61	34	55	59
	None	2	3	3	3	3	0	3	4	3	0	2	8	2	8	3	0	2	4	3	3	3	0
Community Size	<200	57	25	54	60	58	40	58	50	56	58	55	75	54	46	65	21	57	58	56	59	60	35
	>=200	43	75	46	40	42	60	42	50	44	42	45	25	69	31	40	79	44	43	44	41	40	65
	Camp	80	25	10	7	9	1	8	1	10	0	6	4	6	2	9	7	1	5	9	7	10	0

Variables	Values (%)	None (%)		Resource diversification (%)		Crop specialization (%)		Foraging Intensification (%)		Storage (%)		Transhumance (%)		Temporal Migration (%)		Permanent Migration (%)		Exchange Out-settlement (%)		Exchange In-settlement (%)		Reciprocity (%)	
		No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Settlement Types	Homesteads	22	0	17	28	22	20	20	23	21	33	22	17	21	23	23	14	22	21	23	17	22	18
	Hamlet	19	75	16	36	21	10	20	23	21	17	19	33	21	15	19	29	21	20	21	17	20	24
	Village	5	0	55	40	48	50	50	41	48	50	52	8	51	39	49	43	46	52	47	55	47	59
Community Organization	No exogamous Clans	67	75	71	62	66	80	66	72	66	83	67	67	70	58	67	71	66	70	66	72	69	53
	Clans	26	25	20	34	27	20	27	23	27	17	27	17	25	31	26	29	27	25	28	17	26	29
Household Organization	Nuclear	28	0	26	29	27	40	28	27	27	33	27	33	25	28	27	29	24	32	25	38	27	29
	Small Extended	55	50	56	53	55	60	59	36	56	42	56	42	56	50	56	50	51	61	59	41	55	53
	Large Extended	15	50	18	14	17	0	12	36	15	25	15	25	17	12	16	14	22	7	15	21	16	18
Landscape	Aquatic	1	0	0	2	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	9
	Desert	6	0	5	7	6	0	6	5	6	0	5	17	4	15	6	7	4	9	5	10	6	6
	Forest	60	0	54	64	57	7	57	64	55	92	60	42	61	46	58	57	54	64	58	59	59	53
	Grassland	33	75	39	28	34	30	35	27	37	83	34	33	34	35	34	36	40	25	35	31	33	41
	Tundra	1	3	3	0	2	0	1	5	2	0	1	8	1	4	2	0	1	2	2	0	2	0
Distance to coast	Short Distance	17	0	21	10	16	20	16	18	17	17	17	17	19	8	17	14	17	16	17	14	17	12
	Mid Distance	12	0	8	16	10	20	9	18	9	33	12	0	12	8	11	7	10	13	10	14	9	24
	Long Distance	72	100	71	74	73	60	74	64	75	50	71	83	70	85	72	79	73	71	72	72	74	65
Elevation	Low	40	25	48	29	39	50	35	64	38	58	40	33	38	46	40	36	44	34	39	41	41	29
	Medium	36	50	35	38	36	40	40	18	37	33	39	8	38	31	35	43	32	43	36	38	36	41
	High	23	25	18	31	24	10	24	18	25	0	21	50	23	23	23	21	24	21	25	17	23	24
Slope	Low	36	25	38	33	37	20	29	68	35	42	37	25	34	42	35	36	40	29	39	24	38	18
	Medium	31	75	36	28	33	30	36	14	34	17	33	33	32	35	34	21	34	30	29	45	31	47

Variables	Values (%)	None (%)		Resource diversification (%)		Crop specialization (%)		Foraging Intensification (%)		Storage (%)		Transhumance (%)		Temporal Migration (%)		Permanent Migration (%)		Exchange Out-settlement (%)		Exchange In-settlement (%)		Reciprocity (%)	
		No	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**	**No**	**Yes**
	High	32	0	26	38	30	50	34	18	31	33	31	33	33	23	30	43	26	39	32	28	31	29
Mean Annual Temperature	Low	25	25	4	5	4	10	4	5	5	0	2	25	4	4	5	0	15	0	6	0	5	0
	Medium	28	50	25	33	28	30	27	36	29	25	27	33	29	27	26	50	80	58	29	24	26	41
	High	69	25	71	62	68	60	69	59	67	75	70	42	67	70	70	50	5	42	65	76	69	60
CV Annual Temperature	Low	40	0	35	40	38	20	37	36	37	42	37	33	39	27	40	14	39	34	40	24	37	35
	Medium	32	50	39	24	33	30	34	27	33	33	35	10	33	31	31	43	37	27	30	41	33	29
	High	29	50	26	34	28	50	28	36	30	25	27	58	27	42	28	43	23	39	28	34	29	35
Mean Monthly Precipitation	Low	4	33	4	43	21	33	26	63	3	0	4	100	43	73	51	50	39	34	52	50	54	33
	Medium	23	0	11	0	36	0	36	0	62	78	6	0	40	27	40	17	37	27	36	40	37	33
	High	51	50	86	96	43	67	38	38	33	22	89	0	17	0	9	33	23	39	13	10	9	33
CV Annual Precipitation	Low	34	25	33	36	36	10	56	27	35	25	33	42	51	43	37	7	63	41	36	38	34	35
	Medium	35	50	36	34	34	50	32	53	34	50	37	17	34	57	35	43	26	45	35	38	36	35
	High	31	25	31	29	30	40	23	20	31	0	30	42	15	0	28	50	11	14	29	34	31	29
Mean Monthly Productivity	Low	72	100	75	70	3	0	2	7	3	0	1	20	2	14	37	7	16	14	3	0	18	0
	Medium	28	0	25	31	62	83	56	93	62	78	64	60	63	71	35	43	63	43	64	64	46	100
	High	0	0	0	0	33	17	40	0	33	22	33	20	34	14	28	50	21	43	33	27	36	0
CV Annual Productivity	Low	3	0	5	0	67	41	42	44	37	88	41	67	86	75	87	67	83	87	85	86	39	58
	Medium	3	0	5	0	33	32	36	17	34	12	31	33	14	25	13	33	17	13	15	14	34	17
	High	83	100	80	91	0	26	22	39	29	0	27	0	0	0	0	0	0	0	0	0	26	25

This study investigates the impact of the environment on the socioeconomic organisation and subsistence strategies of early agropastoral communities. A machine learning model based on Bayesian networks, learned from information extracted from cross-cultural ethnographical societies, is built to quantify the relationship between multiple variables that could have influenced agropastoral lifestyle. Results evidence the importance of the coevolutionary process between the environment and agropastoral communities in shaping their settlement location, economic behaviour, and social preferences. This project also aims to disseminate the application of Bayesian networks and encourage a debate concerning the use of machine learning methodologies and other computational methods for modelling socioecological questions.

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