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Análisis de datos etnográficos, antropológicos y arqueológicos: una aproximación desde las Humanidades Digitales y los Sistemas Complejos

Autora

VIRGINIA AHEDO GARCÍA

Directores de Tesis

Dr. José Manuel Galán Ordax

Dr. Luis R. Izquierdo Millán

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AUTORIZACIÓN PARA LA PRESENTACIÓN DE LA TESIS DOCTORAL

El Dr. D. José Manuel Galán Ordax y el Dr. D. Luis Rodrigo Izquierdo Millán, ambos miembros del Departamento de Ingeniería de Organización de la Universidad de Burgos

EXPONEN

Que la tesis doctoral titulada "Estudio de datos etnográficos, antropológicos y arqueológicos, una aproximación desde las Humanidades Digitales y los Sistemas Complejos" ha sido realizada por Dña. Virginia Ahedo García dentro del programa de doctorado en "Tecnologías Industriales e Ingeniería Civil", en el departamento de Ingeniería de Organización de la Universidad de Burgos, bajo la dirección de ambos.

Que autorizan a Dña. Virginia Ahedo García a presentar el presente documento como memoria para optar al título de Doctora por la Universidad de Burgos.

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RESUMEN

La llegada de las Ciencias de la Computación, el *Big Data*, el Análisis de Datos, el Aprendizaje Automático y la Minería de Datos ha modificado la manera en que se hace ciencia en todos los campos científicos, dando lugar a su vez a la aparición de nuevas disciplinas tales como la Mecánica Computacional, la Bioinformática, la Ingeniería de la Salud, las Ciencias Sociales Computacionales, la Economía Computacional, la Arqueología Computacional y las Humanidades Digitales –entre otras. Cabe destacar que todas estas nuevas disciplinas son todavía muy jóvenes y están en continuo crecimiento, por lo que contribuir a su avance y consolidación tiene un gran valor científico.

En esta tesis doctoral contribuimos al desarrollo de una nueva línea de investigación dedicada al uso de modelos formales, métodos analíticos y enfoques computacionales para el estudio de las sociedades humanas tanto actuales como del pasado. Más concretamente, contribuimos al avance de dicha línea de investigación a dos niveles diferentes: uno más general y otro más específico. La contribución al nivel más general es fuertemente metodológica, ya que consiste en la aplicación de técnicas de análisis de sistemas complejos a bases de datos estandarizadas e integradoras procedentes de los campos de la Etnografía, la Antropología y la Arqueología, con el fin de explorar, analizar, modelar y/o contrastar diferentes hipótesis y teorías sobre cultura material, dinámicas socio-ecológicas y transiciones sociales y ambientales. El valor científico de esta aportación más general tiene una doble vertiente, ya que, por un lado, el enfoque y la metodología seleccionados son en sí mismos innovadores en estos campos, y por otro, las características propias de los mismos –tales como la existencia de sesgos, la presencia de datos incompletos o el tamaño relativamente pequeño de las bases de datos– hacen que sea necesario adaptar las técnicas de análisis preexistentes o desarrollar otras nuevas.

En lo referente a las contribuciones más específicas, éstas se han materializado en los cuatro artículos que constituyen la presente tesis doctoral. En concreto, cada uno de estos cuatro artículos utiliza técnicas de análisis de sistemas complejos para abordar una serie de preguntas de investigación bien definidas, lo que hace que todos y cada uno de ellos contribuyan al avance de la ciencia de manera explícita. Muy brevemente, los temas tratados en dichos artículos incluyen –pero no se limitan a–: (i) la relación entre movilidad y desarrollo tecnológico en sociedades cazadoras-recolectoras y cazadoras-recolectoras-pescadoras del extremo sur de Sudamérica –artículo 1–; (ii) la determinación de la robustez frente al mecanismo de selección de los resultados obtenidos mediante el modelo ABM "cooperación en condiciones de escasez de recursos" (CURP) –artículo 2–; (iii) el estudio de la relación entre las prácticas de reparto de recursos y las variables socio-ecológicas en una muestra de 22 sociedades de pequeña escala –artículo 3–; y (iv) el estudio transcultural de las estrategias de subsistencia y el contexto socio-ecológico de 1290 sociedades documentadas etnográficamente –artículo 4–.

En síntesis, esta tesis doctoral ilustra tanto el potencial como la utilidad del empleo de herramientas de análisis de sistemas complejos para explorar, analizar y/o modelar diferentes cuestiones de interés en los campos de las Ciencias Sociales Computacionales y las Humanidades Digitales en general, y de la Etnografía, la Antropología y la Arqueología en particular. A su vez, realiza aportaciones relevantes en relación a las distintas preguntas de investigación que aborda y condensa una serie de observaciones y lecciones aprendidas que sin duda serán útiles para futuras investigaciones en esta línea.

Palabras clave: análisis de sistemas complejos, aprendizaje automático, modelado basado en agentes, humanidades digitales, ciencias sociales computacionales, estudios transculturales.

ABSTRACT

The advent of Computer Science, Big Data, Data Analysis, Machine Learning and Data Mining has transformed the way science is done across all scientific fields, resulting as well in the emergence of new computer-based and data-driven disciplines such as Computational Mechanics, Bioinformatics, Health Engineering, Computational Social Science, Computational Economics, Computational Archaeology and the Digital Humanities –among others. Remarkably, these new disciplines are still young and rapidly growing, being thus of great scientific value to contribute to their advancement and consolidation.

In this doctoral thesis we contribute to the progress of a new research line in the use of formal modelling, analytical methods and computational approaches for the study of past and present-day human societies. More precisely, we advance this research line at two different levels: one more general and one more specific. The contribution at the most general level is strongly methodological, as it consists in the application of complex systems analysis techniques to integrative standardised databases coming from the fields of Ethnography, Anthropology and Archaeology, to explore, analyse, model and/or test different theories and hypotheses about material culture, socio-ecological dynamics and social and environmental transitions. The scientific value of this general-level contribution is twofold since, on the one hand, the approach and methodology selected are per se innovative in those fields, and, on the other, the particularities inherent to them –biases, limited size of the databases, missing data, etc.– require the adaptation of pre-existing analysis techniques and/or the development of new ones.

As regards the more specific contributions, they are materialised in the four scientific articles that constitute the present doctoral thesis. In particular, these four articles apply complex systems analysis techniques to address well-defined scientific questions, thus making each of them explicit contributions to the advancement of science. Very briefly, the topics covered in those articles include –but are not limited to–: (i) the relationship between technological development and mobility patterns in hunter-gatherer and hunter-fisher gatherer societies from Southernmost South America –article 1–; (ii) the assessment of the robustness to the selection mechanism of the results obtained with the ABM model ‘cooperation under resource pressure’ (CURP) –article 2–; (iii) the study of the relationship between food sharing practices and socioecological variables in a cross-cultural sample of 22 small-scale societies –article 3–; and the cross-cultural analysis of both the subsistence choices and the socioecological context of 1290 ethnographically documented societies –article 4–.

All in all, this doctoral thesis illustrates both the potential and utility of using complex systems analysis tools to explore, analyse and/or model different questions of interest in the fields of Computational Social Science and the Digital Humanities in general, and of Ethnography, Anthropology and Archaeology in particular. In addition, it provides relevant insights into the specific issues addressed in each of its four articles and condenses a series of observations and lessons learned that will undoubtedly be useful for future research in this line.

Keywords: complex systems analysis, machine learning, agent-based modelling, digital humanities, computational social science, cross-cultural studies.

Si caminas solo, irás más rápido;
si caminas acompañado llegarás más lejos.

Proverbio chino

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If you want to walk fast, walk alone.
If you want to walk far, walk together.

Chinese proverb

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Virginia Ahedo García

CONTENIDO

INTRODUCTION

1. INTRODUCTION

This thesis advances science at two different levels: one more general and one more specific.

The contribution at the most general level consists in the application of formal complex systems analysis techniques to integrative standardised databases coming from the fields of Ethnography, Anthropology and Archaeology. Recall that the scientific value of this general-level contribution is twofold since, on the one hand, the approach and methodology selected are per se innovative in those fields, and, on the other, the particularities inherent to them –biases, limited size of the databases, missing data, etc.– require the adaptation of pre-existing analysis techniques and/or the development of new ones.

On its part, at the most specific level we find not one but four scientific contributions – the four scientific articles that constitute the present thesis. Notably, each of these four articles applies complex systems analysis techniques to address well-defined scientific questions, providing relevant insights into the matters at hand. Very succinctly, the issues covered in those articles include: (i) the relationships between shared technology and mobility patterns in pedestrian and nautical hunter-gatherer and hunter-fisher- gatherer societies from Southernmost South America –article 1–; (ii) the robustness to the selection mechanism of the results obtained with the ABM model ‘cooperation under resource pressure’ (CURP) –article 2–; (iii) the study of the relationship between food sharing practices and socioecological variables in a cross-cultural sample of 22 small-scale societies –article 3–; and (iv) the analysis of both the subsistence choices and the socioecological context of 1290 societies documented in the Ethnographic Atlas (Ethnographic Atlas, 1962; Murdock, 1967; Gray, 1998) to shed light into the variability and viability of the different subsistence choices and to explore the role played by the ecological setting and/or fishing in the configuration of the different subsistence economies –article 4–.

1.1 MOTIVATION

We live in the era of Computer Science, Big Data, Data Analysis, Machine Learning and Data Mining. Noteworthily, the capacity to produce, collect and analyse unprecedented amounts of data has transformed the way science is done across all scientific disciplines, albeit at different paces.

In disciplines such as Physics and Biology, the availability of massive amounts of data together with the adoption of advanced computational approaches and the development of complex systems analysis techniques has resulted in the emergence of brand new disciplines such as Computational Mechanics, Computational Biology, Health Engineering, etc., and in the attainment of relevant scientific breakthroughs.

In other disciplines such as the Social Sciences and the Humanities, however, the integration of the Information and Communication Technologies (ICT) and the application of computational methods has been much slower (Lazer et al., 2009). As a matter of fact, whilst disciplines such as Computational Social Science and the Digital Humanities have also emerged, to this day they are still facing major challenges (Conte et al., 2012; Caro et al., 2020), and substantial barriers continue to limit their progress (Lazer et al., 2020).

Remarkably, in the fields of Ethnography, Anthropology and Archaeology the adoption of computational approaches and the use of the formal complex systems analysis tools is even more scarce, being significantly limited the number of research groups that have successfully conducted research projects in this line (Madella, 2020). In this vein, particularly worthy of mention is the SimulPast project –Social and environmental transitions: Simulating the past to understand human behaviour (CSD2010-00034 CONSOLIDER-INGENIO 2010)–, a pioneering project that was aimed at the development of an innovative and interdisciplinary methodological framework for the modelling and simulation of past societies and their interactions with the environment, and which laid the foundations for this type of research.

For all the above reasons, the value of contributing to the advancement and consolidation of a new research line in the use of formal modelling, simulation and analytical approaches to investigate past and present-day human societies seems evident, even more so when certain authors such as Conte et al. (2012) consider that it is precisely the combination of advanced computational approaches with a sensible use of experiment and/or the exploitation of comprehensive standardised databases that has the potential to induce a paradigm shift in the Social Sciences. This thesis is a contribution to this promising line of research.

1.2 OBJECTIVES

The present thesis is entitled: “Analysis of Ethnographic, Anthropological and Archaeological data: a Digital Humanities and Complex Systems approach”. Therefore, it is developed at the interface between the Digital Humanities, Computational Social Science and Complex Systems analysis.

More specifically, its overarching goal is the application of complex systems analysis techniques and methodologies to comprehensive standardised databases from the fields of Ethnography, Anthropology and Archaeology, to explore, analyse, model and/or simulate different theories and hypotheses about material culture, socio-ecological dynamics and social and environmental transitions.

Notably, such general objective can be broken into the following general sub-objectives:

- Contribute to the development and application of new formal methodologies aimed at the analysis and integration of primary research evidence, which in the fields of Ethnography, Anthropology and Archaeology is particularly fragmentary and limited.

- Analyse comprehensive standardised databases such as the publicly available D-PLACE database –i.e., the Database of Places, Language, Culture, and Environment– (Kirby et al., 2016), and/or other relevant databases developed by the experts in the field of interest –be it Ethnography, Anthropology or Archaeology– to assess the validity of certain prevailing hypotheses and theories in the light of the evidence available.
- Illustrate the utility of cross-cultural quantitative approaches to conduct data-driven hypotheses testing and/or as theory-building tools.
- Explore the potential of computer simulation in general, and of Agent-Based modelling (ABM) in particular, for the explanation of complex social systems and dynamics. In this vein, if simulation is to be used for theory-building purposes, the robustness of the findings obtained will have to be systematically assessed. This latter aspect is precisely one the specific objectives of this thesis, since we intend to assess the robustness to the selection mechanism of the results obtained with the ‘cooperation under resource pressure model’ (CURP) (Pereda et al., 2017b) before further exploring the archaeological implications that its results may have.
- Integrate complementary analytical approaches –when possible and of interest– so as to ensure that the knowledge obtained is as rigorous and comprehensive as possible. An illustrative example of what is meant by this sub-objective would be the assessment of the existence of a possible relationship between variables by means of network modelling, machine learning techniques, the calculation of relevant statistics, etc.

Noteworthily, the above-described global objective and its sub-objectives have been materialised in the four scientific articles that constitute the present thesis, namely:

- **Article 1:** Briz i Godino I, Ahedo V, Álvarez M, et al. (2018): Hunter–gatherer mobility and technological landscapes in southernmost South America: a statistical learning approach. Royal Society Open Science 5(10): 180906. DOI: 10.1098/rsos.180906.
- **Article 2:** Zurro D, Ahedo V, Pereda M, et al. (2019): Robustness assessment of the ‘cooperation under resource pressure’ (CURP) model. Hunter Gatherer Research 3(3): 401–428. DOI: 10.3828/hgr.2017.20.
- **Article 3:** Ahedo V, Caro J, Bortolini E, et al. (2019): Quantifying the relationship between food sharing practices and socio-ecological variables in small-scale societies: A cross-cultural multi-methodological approach. Albuquerque UP (ed.) PLOS ONE 14(5): e0216302. DOI: 10.1371/journal.pone.0216302.
- **Article 4:** Ahedo V, Zurro D, Caro J, et al. (2020): Let’s go fishing: a quantitative analysis of subsistence choices with a special focus on mixed economies among small-scale societies (currently under review).

Recall that aside from these more general objectives, each one of the four scientific articles has its own specific objectives as well, the latter being related to the particular research question(s) addressed. For the details on the specific objectives of each of them, please refer to the chapter corresponding to each article.

1.3 APPROACH AND METHODOLOGY SELECTED

As stated in its title, the present thesis presents a Digital Humanities and Complex Systems approach. Given that its intended purpose is the analysis of ethnographic, anthropological and archaeological data –all the three disciplines belonging to the realm of the Social Sciences and the Humanities–, that our focus is on comprehensive integrative databases duly digitalised and standardised, and that social systems constitute one of the most archetypal examples of complex systems (Conte et al., 2012; De Domenico et al., 2019), the approach selected seems a priori appropriate for the declared objectives.

In strictly methodological terms, even though the different methodologies and analytical techniques used in the present thesis come from different scientific fields –see Management Engineering, Computer Science, Physics, Mathematics and Statistics, among others–, the fact is that they can be regarded more generally as a set of tools useful for the analysis of complex systems –what we call *the complex systems analysis toolbox*. (Note that in the present thesis we have included under the term *complex systems analysis toolbox* all those methodologies and techniques that are relevant for the previously stated research purposes; consequently, the list provided is by no means exhaustive and may be pertinently completed in the context of other research fields and/or applications).

More specifically, under the umbrella of the complex systems analysis toolbox we have included: modelling in general and ABM in particular, the Network Science paradigm and Machine Learning techniques –both supervised and unsupervised–. (For more details on each of these analytical frameworks and their specific tools please refer to the Methodological Framework chapter, where they are thoroughly explored). Remarkably, the choice of those tools was made on grounds of their complementarity –the different frameworks allow us to explore distinct aspects of the same problem– and of their potential utility to answer the research questions at hand.

Ultimately, recall that, as noted in the Introduction, the use of this methodology in the fields of Ethnography, Anthropology and Archaeology is in itself innovative –regardless of the results that it may provide–, and that it may be necessary to adapt pre-existing analysis techniques or to develop new ones to address the issues derived from the particularities of these fields.

1.4 SPECIFIC CONTRIBUTIONS

Given that, as previously explained, this thesis presents objectives at two well-defined levels –that is, the overall objective and the article-specific objectives–, its main scientific contributions are also circumscribed to these two levels. Thereupon, here we will distinguish between the overall contribution of the thesis and the specific scientific contributions of each article –article-specific contributions–.

OVERALL CONTRIBUTION

The overall contribution of the present thesis is strongly methodological, as it responds to its overarching aim of applying advanced complex systems analysis techniques to duly formalised and standardised broad-spectrum databases coming from Ethnography, Anthropology and Archaeology. More specifically, in this thesis we have explored the following two databases:

- Binary Database of Patagonian Archaeological Technology, which is publicly available at https://royalsocietypublishing.org/doi/suppl/10.1098/rsos.180906. Please note that the bibliography and reports used to generate the original database –namely the Reference Database of Hunter-Gatherer Technology from the uttermost tip of Patagonia (South America)– are also publicly available and can be consulted at any time at: https://www.researchgate.net/publication/324217985_Reference_Database_of_Hunter-Gatherer_Technology_from_the_uttermost_tip_of_Patagonia_South_America. This is the database that was analysed in article 1.
- Database of Places, Language, Culture and Environment –D-PLACE– (Kirby et al., 2016), which contains cultural, linguistic, environmental and geographic information of over 1400 human societies, and which is publicly accessible at: https://d-place.org/. D-PLACE was used in articles 3 and 4.

As regards the complex systems analysis tools applied within the framework of this thesis, they include: (i) modelling in its broadest sense –recall that we adhere to the assertion by Izquierdo et al. (2008) that everything in science can be regarded as a model–; and, more specifically: (ii) ABM modelling and the artefact detection procedures proposed by Galán et al. (Galán et al., 2009, 2013) –article 2–; (iii) supervised learning classification algorithms –articles 1 and 4–; (iv) supervised learning regression algorithms –article 3–; unsupervised learning clustering techniques –article 4–; individual and group variable importance analyses –articles 1 and 4–, network modelling as a formalisation procedure –article 3–; and the following exploratory statistical metrics: Maximal Information Coefficient –MIC– (Reshef et al., 2011), Distance Correlation –dCor– (Székely and Rizzo, 2009) and Heller-Heller-Gorfine measure –HHG– (Heller et al., 2013), –the three of them used in article 3–.

As already mentioned, the use of these formal complex systems analysis tools to explore integrative standardised databases from Ethnography, Anthropology and Archaeology is in itself innovative and may imply the adaptation of some of them and/or the development of new ones. More precisely, such innovative nature has two facets: on the one hand, it is innovative in the most obvious sense, that is, since computational and formal quantitative approaches are still rarely used in mainstream research in Ethnography, Anthropology and Archaeology; and, on the other hand, it is innovative in the sense that these methodologies enable and facilitate the conduction of cross-cultural studies –i.e., systematic comparisons of different societies/cultures that seek for general principles and/or universal explanations and that are heavily reliant on quantitative and statistical methods– which, in turn, are held to be key for the future of the Social Sciences in general, and of Ethnography, Anthropology and Archaeology in particular (Ember and Ember, 2009). Recall that the potential and scientific relevance of cross-cultural research lies in the fact that their results are likely to be more generally valid and trustworthy than single-case studies and/or untested theories (Ember and Ember, 2000). Notably, in this thesis two out of the four articles constitute cross-cultural studies –articles 3 and 4–.

Therefore, for all the above reasons, the overall-level contributions of the four articles constituting this thesis may be summarised as follows:

- Articles 1, 2, 3 and 4 contribute to the advancement of science by the application of advanced complex systems analysis tools in the fields of Ethnography, Anthropology and Archaeology, since such sophisticated approaches are not common in these three disciplines, and because their adoption enforces alternative conceptualisations and/or the use of specific tools –such as missing data imputation procecures– to cope with the particularities of those fields.
- Articles 3 and 4 make a second general contribution in relation to cross-cultural research. More specifically, they illustrate the potential and usefulness of complex systems analysis tools for the conduction of cross-cultural studies, and thus for the advancement of cross-cultural research.

ARTICLE-SPECIFIC CONTRIBUTIONS

In this section we list very briefly the specific contributions to the advancement of science made by each of the four articles of the thesis. For a more detailed description of these contributions please refer to the full articles.

ARTICLE 1 – "HUNTER–GATHERER MOBILITY AND TECHNOLOGICAL LANDSCAPES IN SOUTHERNMOST SOUTH AMERICA: A STATISTICAL LEARNING APPROACH":

- It demonstrates the existence of a strong non-trivial relationship between technology and mobility patterns in the archaeological sites that are compiled in the Binary Database of Patagonian Archaeological Technology. In other words, it evidences the existence of technological knowledge specific to each mobility type.
- It highlights the relevance of the processes underlying the production of artefacts as reliable markers of technological development and social interaction. More precisely, in accordance with the variable importance analyses conducted, productive techniques are in fact more discriminant than functional requirements and the final shape of the artefact –both traditionally considered to be the key markers.

- It identifies the occupations that are misclassified by the algorithms as potential geographical areas of interaction between nautical and pedestrian societies.

ARTICLE 2 – "ROBUSTNESS ASSESSMENT OF THE 'COOPERATION UNDER RESOURCE PRESSURE' (CURP) MODEL":

- It demonstrates that the 'cooperation under resource pressure' ABM model leads to the same persistent regimes regardless of the selection mechanism imposed. Consequently, this work deepens our understanding of the CURP model and increases our confidence in its results.

ARTICLE 3 – "QUANTIFYING THE RELATIONSHIP BETWEEN FOOD SHARING PRACTICES AND SOCIO-ECOLOGICAL VARIABLES IN SMALL-SCALE SOCIETIES: A CROSS-CULTURAL MULTI-METHODOLOGICAL APPROACH":

- It identifies a generalised lack of statistically significant relationships between the food sharing practices and the socio-ecological variables of the 22 small-scale societies considered in the study.
- It constitutes a potential falsifier of the hypothesis that the food sharing practices of geographically closer societies may be more similar, as none of the analyses conducted in this work support it.

ARTICLE 4 – "LET'S GO FISHING: A QUANTITATIVE ANALYSIS OF SUBSISTENCE CHOICES WITH A SPECIAL FOCUS ON MIXED ECONOMIES AMONG SMALL-SCALE SOCIETIES":

- This work identifies recurrent specific subsistence combinations in a dataset of 1290 ethnographically documented societies, which illustrates that not all possible subsistence combinations are viable.
- It proposes a formal quantitative criterion –the information entropy– to determine whether a subsistence combination is mixed: the higher the information entropy, the more mixed the economy.
- It evidences that, contrary to previously thought, mixed economies are not a marginal choice, as they constitute up to 25% of the cases in the database considered. Besides, mixed economies are found to present multiple manifestations and significant internal variability.
- It shows that specific subsistence combinations appear recurrently in certain ecological systems.
- Its results do not support the traditional relegation of fishing to a marginal role. Actually, fishing is found to be present in 60% of the recurrent subsistence combinations identified, which suggests that it could in fact be more relevant than previously thought.

- It reveals that fishing is the common denominator across all mixed economies, which suggest that it may play a key role in their configuration.

1.5 OUTLINE OF THE THESIS

The present thesis is structured in six chapters (Fig. 1). The first two chapters –Introduction and Methodological Framework– constitute the first section, which is devoted to the explanation of its **theoretical foundations**; more precisely, the Introduction chapter provides a general overview of the entire thesis –its motivation, objectives, the approach and methodology selected, its specific contributions and the outline of the document–, while the Methodological Framework chapter explores thoroughly the different methodological aspects. As regards the second section, it consists of the four **scientific articles** produced within the framework of the present doctoral thesis. In particular, each of the articles constitutes a separate chapter, being thus section two composed of four chapters –chapters three, four, five and six–. Eventually, section three consists of a single chapter that contains the **general conclusions**, the potential and limitations of the different approaches and a list of worthwhile further research lines.

More specifically, **chapter one** constitutes the roadmap of the thesis, as it covers all its stages but in a very succinct manner. Thereupon, its purpose is merely introductory, being it necessary to refer to the subsequent chapters for the details.

Chapter two contains a detailed exploration of the different methodological aspects. In particular, it consists of different blocks, being each one of them dedicated to a concept, analytical framework or methodology that deserves individual consideration. Therefore, it serves no other purpose than reviewing the specifics and implications of each term/tool/approach, so that the four scientific articles can be fully understood and adequately placed into context.

This chapter follows a logical structure that goes from the general to the particular; more precisely, it starts by providing a general perspective of the different fields involved in the thesis –namely the Digital Humanities (DH), Computational Social Science (CSS) and Complex Systems– and of the interrelations between them, to subsequently explore the different approaches, frameworks, methodologies and tools that may be used for the analysis of the different problems, systems and/or research questions that we will find at their intersection.

Therefore, strictly speaking, the methodological framework itself starts only after we have finished explaining and clarifying the details and main differences between the DH, CSS and Complex Systems analysis. More specifically, it begins with a general description of the scientific method and with a detailed review of its evolution throughout history, to conclude that even though there exists a common set of scientific principles and practices that are shared across all disciplines –objectivity, systematic nature, reproducibility, replicability and falsifiability–, in actuality no universal scientific method exists, being it markedly discipline-specific. In accordance with such a particularistic approach to method, the next block is devoted to the details of the scientific method of the Complex Systems field. Importantly, as previously noted, rather than a specific scientific method per se, the Complex Systems field presents an analytical toolkit consisting of different approaches, methodologies and techniques that are either general-purpose or discipline-specific, and whose utility is strongly dependent on the problem under consideration and on the intended future application.

From this point forward, chapter two focuses on the different components of the complex systems analysis toolbox. Concretely, in keeping with our approach from the general to the particular, we first explore modelling as a scientific tool and some of the most common modelling purposes, to subsequently move into the ABM paradigm, the Network Science discipline and the different Machine Learning approaches and techniques. In all cases, the explanation of the different tools and methodologies is illustrated with application examples extracted from the four scientific articles of the thesis.

Chapter three consists of the first scientific article of the thesis, namely “Hunter–gatherer mobility and technological landscapes in southernmost South America: a statistical learning approach” (Briz i Godino et al., 2018), which applies statistical learning techniques to study the relationship between mobility types –nautical vs. pedestrian–, technological features and shared technological knowledge in pedestrian hunter-gatherer and nautical hunter-fisher-gatherer societies from southernmost South America.

Chapter four contains the second article of the thesis, namely “Robustness assessment of the ‘cooperation under resource pressure’ (CURP) model” (Zurro et al., 2019). This contribution assesses the robustness to the selection mechanism of the results obtained with the previously published CURP model (Pereda et al., 2017b) –an ABM model designed to explore the different behaviours that emerge in societies lacking food preservation technologies when they are faced with food stress episodes.

Chapter five presents the third scientific article of the thesis: “Quantifying the relationship between food sharing practices and socio-ecological variables in small-scale societies: A cross-cultural multi-methodological approach” (Ahedo et al., 2019). This work embraces a multi-methodological quantitative approach to ascertain if the differences observed between the food sharing practices of the 22 socities included in the study can be ascribed to local adaptation.

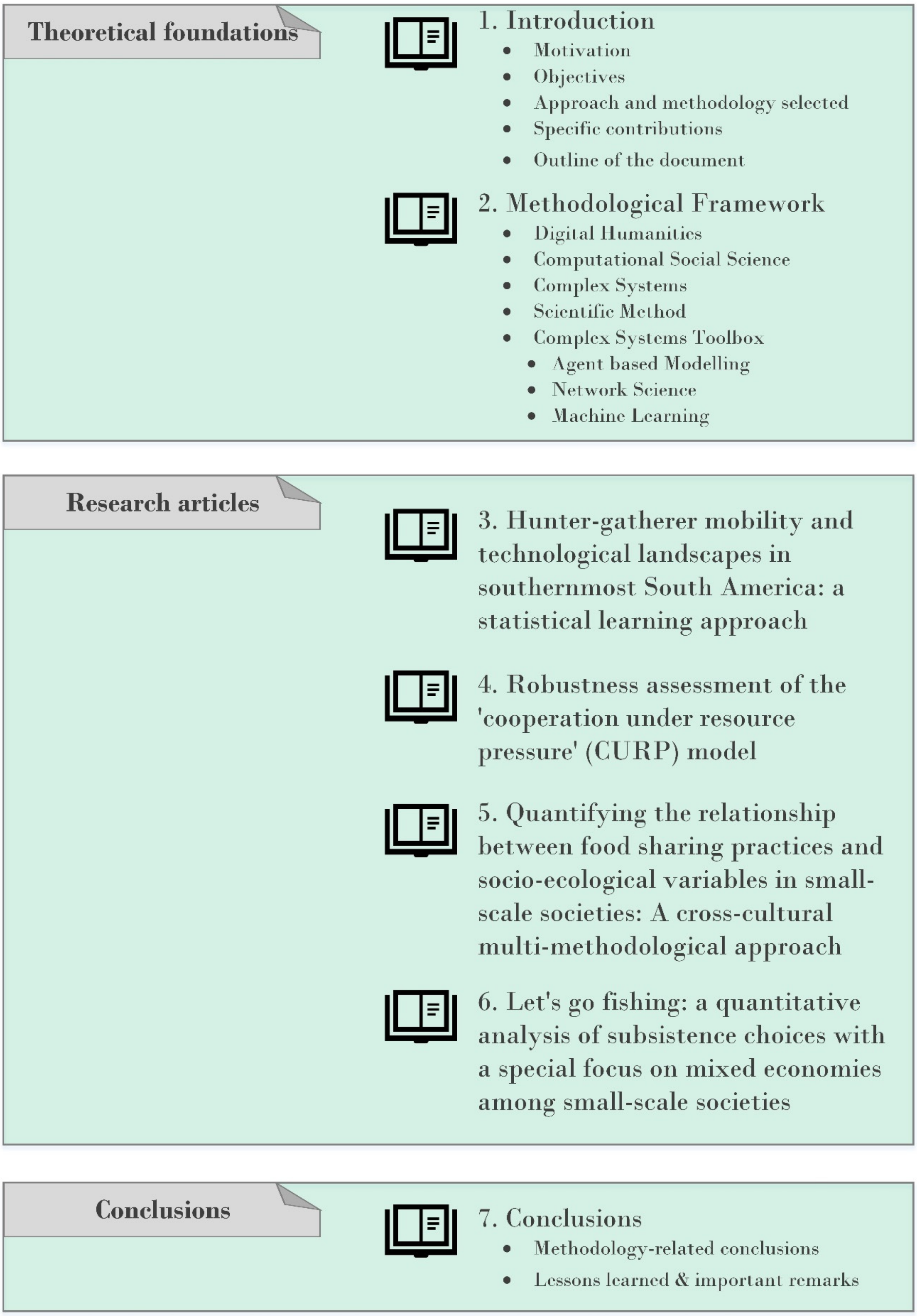

Fig. 1. Outline of the present thesis (document structure).

Chapter six consists of the fourth and last article of the thesis, namely “Let’s go fishing: a quantitative analysis of subsistence choices with a special focus on mixed economies among small-scale societies” (currently under review). In this last article, a machine learning approach is selected to explore and analyse both the subsistence economies and the socioecological context of 1290 ethnographically documented societies. The purpose of these analyses is threefold: (i) increasing our understanding of the variability and success of the different subsistence combinations; (ii) evaluating the impact of the environmental setting in the configuration of the different subsistence choices; and (iii) exploring the role of fishing in the development of long-term successful alternatives to agriculture.

Chapter seven summarises the main conclusions of this thesis around two levels of resolution: methodology-related conclusions and lessons learned & important remarks. Ultimately, future research lines/issues of potential interest are proposed.

METHODOLOGICAL FRAMEWORK

2. METHODOLOGICAL FRAMEWORK

2.1 DIGITAL HUMANITIES, COMPUTATIONAL SOCIAL SCIENCE AND COMPLEX SYSTEMS

As outlined in its title, the present thesis is developed at the interface between the Digital Humanities, Computational Social Science and Complex Systems analysis. Therefore, we will firstly review the specifics and implications of each term, so that the four journal articles constituting it can be fully understood and adequately placed into context.

DIGITAL HUMANITIES

The Digital Humanities (DH) are often described as the use of digital tools –generally computers– to conduct humanistic work (Gonzalez-Perez, 2020). Under this standpoint, the far-reaching changes that have taken place in the digital realm over the last decades would have prompted a paradigm shift in the Humanities consisting not only in the use of new tools and technologies to undertake research, but also in the change of the subjects of study and the ways to approach them (Berry, 2012).

It is important to note that since their emergence, there has been much debate on whether the DH should be considered a field in its own right. Such a discussion stems mainly from two distinct facts: (i) the Humanities being a broad term that encompasses many fields –Ancient and Modern Languages, Literature, Philosophy, Archaeology, History, Anthropology, Law, Politics and Art, among others; and the DH being conceived as the intersection between Humanities research and Computer Science (Su et al., 2020). As Svensson (2010) put it, the DH can be assumed to comprise a field in a loose sense, i.e., rather than an independent and well-delimited academic field outside the traditional Humanities, the DH should be seen as an inclusive notion involving different principles, initiatives and activities aimed at the integration and/or successful collaboration of the Humanities and the ICT. Alternatively, other authors portray the DH as a *transdiscipline* in the sense that it transcends the traditional dichotomies between Sciences vs. Arts, theory vs. practice and the quantitative vs. the qualitative, as it comprehends not only the Social Sciences, the Humanities and computational and statistical methods, but also the formulation of integrative approaches, the development of new epistemological frameworks, the emergence of new objects of interest, and a series of values and good practices that are shared by the DH community (Castro, 2013; Galech Amillano, 2020).

As a matter of fact, the DH constitute a relatively new and still emergent domain that has been undergoing constant re-evaluation and redefining since its inception (Su et al., 2020). To this day, there exists no consensus as to how to define them or the different typologies of the DH. Consequently, any attempt at mapping the DH will constitute just a particular reading and interpretation of them (Svensson, 2010). Therefore, it is important to clarify what we understand by DH in the present thesis. Particularly, we step aside from the debate on whether the DH should be considered a field or not, and conceive them as an umbrella term that encompasses the application of different kinds of methodologies coming from the Statistical and Computational Sciences –such as digitalisation processes, Machine Learning, Data Mining, Natural Language Processing, etc.– to the study of all kinds of theories, problems and hypotheses coming from the Social Sciences and the Humanities. We agree with Castro (Castro, 2013) that the defining traits of the DH are its interdisciplinary nature and the set of principles, procedures and values that are shared by the DH community: collaboration, cross-sectional dialogue, joint development of models/tools/conceptualisations/frameworks to address larger-scale problems, open source code and open data to ensure replicability of results, etc.

An important remark regarding the DH is that as a consequence of their cross-disciplinary nature, they draw on manifold epistemic traditions, being thus not a trivial endeavour to find common ground and language. In fact, DH projects usually need longer execution periods than the traditional disciplinary ones precisely for those reasons, since training time is required so that the different researchers involved can better understand each other's disciplines, find a common language and create a common arena from which to transcend the disciplinary boundaries.

Hereafter we provide a list of some of the technologies and methodologies typically involved in the DH –please recall that it is not exhaustive and that its purpose is merely illustrative: digitalisation, i.e., data –visual, textual, audio– encoding, recording and storage, together with the development of data consultation systems; digital labelling systems; geographical information systems (GIS); social network analysis; data analysis and data modelling; etc.

Lastly, we would like to comment on the visionary and forward-looking sentiments associated with the DH. As Svensson (2012) put it, the DH are key to stimulate transformative thinking, far-reaching discussions, innovation, reconfiguration and exploration thanks to their broad and intersectional reach, and the multifarious possibilities that both digitalisation and technical developments offer to the field. In particular, the DH can be seen as the laboratory and means for thinking about the state and future of both the Social Sciences and the Humanities. Remarkably, such feeling is shared by the different DH international associations –The Association for Computers and the Humanities (ACH), the Alliance of Digital Humanities Organizations (ADHO), the European Association for Digital Humanities (EADH), the Canadian Society for Digital Humanities (CSDH), the Australasian Association for Digital Humanities (aaDH), the Japanese Association for Digital Humanities (JADH)– and by many governmental research institutions –such as the EU– that already include in their middle-term objectives and directives the need for transdisciplinary research and the development of the DH (Horizon 2020 - FET Open - Research and Innovation Actions (RIA)).

COMPUTATIONAL SOCIAL SCIENCE

Computational Social Science (CSS) is one of the most prominent disciplines under the umbrella of the DH. In the last decade, it has experienced an unprecedented boost as a result of both the continuously evolving capacity to collect, process, analyse and store massive amounts of data on social phenomena, and the urgent need to understand the ever-increasing complexity of our interconnected society to assist policy makers (Conte et al., 2012).

Briefly put, CSS is the ICT-enabled study of social phenomena (Lazer et al., 2009). More specifically, it can be defined as the discipline that brings together Complex Systems Science, Computer Science and the Social Sciences, thus providing an innovative integrative approach to human and social behaviour, and enabling the analysis and exploration of social and economic processes at different scales of resolution (Caro et al., 2020).

In strictly methodological terms, it is interesting to note that CSS encompasses at the same time two distinct approaches: on the one hand, it presents a data-analysis-oriented side aimed at identifying previously unknown patterns/relationships by exploiting the vast datasets of digital footprints currently available; and, on the other hand, it is a model-oriented discipline that seeks to produce models for different purposes, being prediction and explanation the most common aims (Conte et al., 2012). Note that the two approaches are not mutually exclusive, and thus it may be of interest to combine them whenever possible.

According to the current state of the art, CSS has traditionally and mostly dealt with: (i) the study of emergent phenomena at the aggregate level –i.e., stable macroscopic patterns arising from the local interaction of individual entities–, particularly emergent social behaviours (cooperation, reciprocity, altruism), emergent social aggregates (segregation, coalitions) and institutions (markets, modern states); and (ii) social learning systems and mechanisms (reinforcement, imitation).

As regards its future research directions, thanks to the new channels for research provided by technological development and the digitalisation of human behaviour, the CSS haare now considered key to address the big societal problems of the 21st century and to have the potential to re-found the science of society. Among the most pivotal research challenges that CSS is expected to address are (Conte et al., 2012):

- *Understanding levels and directions of interaction*. Complex social systems are characterised by multiple ontological levels with multidirectional connections. The most archetypal approximation consists in reducing them to the micro and macro levels; however, in many cases such an approach is insufficient, as it implies disregarding all intermediate levels such as groups, networks, communities, etc. In addition, entities belonging to the different levels interact with one another and also with entities at any other level, thus complicating the analysis and understanding of the system. Therefore, even though emergence has been much studied, further research is needed to understand how social levels emerge from one another, and to shed light on the inter- and intra-level interactions and their effects.
- *The development of hierarchical and multilevel cultural models,* that is, of models that incorporate different cultural traits with different dynamical processes at different scales. This second challenge is very closely related to the previous one and is necessary to overcome the limitations of more traditional approaches that are either focused on a single cultural feature or consider various cultural traits at the same level.

- *The integration of experimental work with simulation*. Such an approach will prove extremely useful in the Social Sciences. Nevertheless, to ensure its success, a careful Design of Experiments (DoE) will be needed. More specifically, different research objectives will require different DoE, being the most likely scenarios: (i) DoE to test inferences from data, (ii) DoE to test simulation predictions, (iii) DoE to assess insights derived from a given model –which requires the insights to be empirically testable–, (iv) DoE to address the formation of the social interaction framework, and (v) design of large-scale laboratory experiments. Remarkably, even if the five purposes described pose a challenge, the latter case is the most challenging of all of them; in fact, there is a need for commonly agreed protocols with repeatable procedures and controlled environments, so that virtual laboratories can successfully handle large numbers of volunteers interacting through ICT media.
- *The integration of heterogeneous models for the analysis and modelling of large-scale social systems*. In particular, the analysis of complex social systems should be supported on three main cornerstones: (i) empirical data analysis, as it may reveal unknown relationships and/or statistical features that can subsequently be used as inputs/outputs of the model; (ii) analytical modelling, i.e., the development of simplified models amenable to mathematical analysis that reproduce the stylised facts empirically observed; notably, the study of such analytical models may provide valuable insights into the phenomenon under scrutiny and/or guide future research by pointing to regions/directions of potential interest; and (iii) ABM models and simulations. ABM allows for more complex models, hence being potentially more realistic and enabling the inclusion of dynamics/effects previously identified via data analysis/analytical modelling. Nonetheless, as a consequence of their greater complexity, ABM models are generally mathematically intractable, being thus explored through numerical simulation; once simulation results are obtained, they can be subject to empirical validation and/or examined via data analysis. Additionally, it is important to note that the integrative modelling enterprise is related as well to the use of tools and concepts coming from disciplines as varied as Physics, Mathematics, Economics, Computer Science, etc., throughout all the stages of the modelling process.

Notably, alongside the aforementioned research challenges that the CSS field is expected to address, there exist additional operational challenges that will need to be tackled (Lazer et al., 2009, 2020):

- *Multidisciplinary research*. CSS is a multidisciplinary field. However, the multidisciplinary endeavour is not easy for reasons that range from the complexities inherent to conducting cross-disciplinary research –namely the necessity of training to get to understand each other, the lack of a common language, the need to transcend disciplinary boundaries and to develop a common ground from which to work on shared objectives, etc.– to the insufficient support coming from research institutions as a consequence of their decentralised budgeting models –which discourage collaboration– and of their evaluation and promotion procedures –which tend to underappreciate multidisciplinary scholars.

- *Inadequate computational research infrastructures* to comply with the requirements of security (sensitive datasets), computational power necessary to conduct large-scale analysis on social data, and access to a large number of researchers/volunteers.
- *Inadequate data-sharing policies*. Even though there have been successful collaborations with governmental institutions, access to data from private companies is rarely available to academics and if so, it is often subject to non-disclosure agreements and/or incurs in conflicts of interest. As a result, there are two main risks that deserve further consideration:
    1. Given the voluntary nature of the collaboration between private companies and scientists, data availability is subject to arbitrary and unpredictable decisions by private actors, which renders the science produced this way potentially unreliable –it can present multiple biases.
    2. The exploitation of data generated by consumer platforms may be unrepresentative of the entire population, as those platforms were never designed for research purposes. In addition, since platform owners are not incentivised to maintain instrumentation consistency for the benefit of research, they can alter it at any time in the pursuit of their private interests.
- The lack of commonly agreed protocols on how to collect and analyse digital personal data while preserving privacy and ensuring security. The elaboration of some public guidelines in this regard would assist academic institutions from all over the world in both the development of their CSS research and in the implementation of their own data policies, which would undoubtedly pave the ground for future large-scale investigations.

COMPLEX SYSTEMS

In recent years, Complex Systems research is becoming increasingly popular as it is necessary to address the large-scale problems of the 21st century: epidemics, economic crisis, climate change, etc. Nevertheless, there is no concise definition of a complex system on which all scientists agree (Ladyman et al., 2013). In the present thesis, we will make use of one of the most recent attempts to define Complexity Science and complex systems, namely that of De Domenico et al. (2019) in the booklet “Complexity Explained”:

Complexity Science, also called Complex Systems Science, studies how a large collection of components – locally interacting with each other at the small scales– can spontaneously self-organise to exhibit non-trivial global structures and behaviours at larger scales, often without external intervention, central authorities or leaders.

Complex systems are characterised by the fact that the properties of the collection of components may not be understood or predicted by the study of its constituents alone, as such components interact with each other and potentially with the environment in multiple ways.

To better understand complex systems, let us briefly review some of the key ideas and related concepts as covered by De Domenico et al. (2019)*:*

- **Interaction.** Complex systems are often characterised by the interaction of their constituents with each other and/or with the environment. Generally, such interconnections form networks of interactions. In this vein, it is worth highlighting that the main challenge of Complex Systems Science is to understand how the different interactions give rise to the global phenomena observed.
- **Emergence.** When dealing with complex systems, an analysis exclusively focused on the individual parts of the system or on their aggregation is insufficient, as "the whole is more than the sum of its parts". This is because of the phenomenon known as *emergence,* which is typically described as involving diverse mechanisms that cause the local interactions between a system's components to produce new information and exhibit non-trivial collective structures at larger scales. Remarkably, such bottom-up emergent phenomena are also often characterised by their non-intuitiveness.
- **System dynamics.** Complex systems are frequently non-linear, which implies that they change at different paces depending on their states and their environment. Recall that non-linear dynamics are usually related to thresholds of certain variables –values that once passed trigger some kind of change– and/or to tipping points of the system –i.e., a critical point after which the system changes radically and potentially irreversibly into a different equilibrium state. In addition, complex systems can present path-dependence, i.e., the attainment of a future state depends not just on the present state but on the whole history of states. Ultimately, there are also some complex systems that are termed *chaotic* since they are highly sensitive to small perturbations and extremely unpredictable in the long term, showing the renowned butterfly effect.
- **Self-organisation.** The concept of self-organisation is very closely linked to the phenomenon of emergence. In fact, the mechanisms by which the interactions between a system's components may produce a global pattern are usually referred to as *self-organising mechanisms,* as there is no central or external controller, being the control of the system distributed across its constituents and integrated through their interactions.
- **Adaptation.** Complex systems may adapt –that is, change their behaviour to ensure survival or to improve their chances of success– through learning or evolutionary processes (Mitchell, 2009). In those cases, they are termed complex adaptive systems.
- **Universality.** A bedrock of Complexity Science is universality, i.e., the notion that many systems in different domains exhibit phenomena with common underlying features, hence being it possible to describe them using the same scientific models.

From all the above, it becomes clear that the study of complex systems requires a multidisciplinary approach. More precisely, it integrates tools and concepts coming from Applied Mathematics, Statistical Physics, Computer Science and Theoretical Economics – among others. In particular, the methodological frameworks and analytical tools most commonly used in complex systems research include: data analysis –Big Data, Machine Learning, Artificial Intelligence–, modelling in general and ABM in particular, numerical simulation, Network Theory and Game Theory.

2.2 THE SCIENTIFIC METHOD

The scientific method is generally defined as the set of practices and techniques that are used to obtain valid scientific knowledge. Notably, at present, it is generally agreed that there exists no such thing as a unique scientific method that applies to all sciences at all historical stages (Chalmers, 2013; Andersen and Hepburn, 2015). In fact, scientific activity varies so much across disciplines and over time that there is increasing consensus that each scientific field should be better thought of as having its somewhat particular scientific method. Nevertheless, this has not been the prevailing view throughout the entire history of science and of philosophy of science. Quite the opposite, the study of the scientific method has given rise to intense debates on its existence, uniqueness and distinctiveness, as well as on its characteristics and role within the scientific enterprise.

Throughout most of the history of science, science has been customarily characterised by its method, which has been held responsible for its success and for the higher status conveyed to scientific knowledge. Remarkably, those ideas seem to have percolated into our present-day conception of science, since, as evidenced by Andersen and Hepburn (2015), the idea of *the* scientific method still figures prominently in current science education, as well as in contemporary discourse on many different topics both within science and in society at large –see for instance the IMRAD paper structure (Introduction, Method, Results, Analysis, Discussion) recommended by certain scientific journals, and the widespread use of the scientific method as a way of demarcating scientific activity from non-science.

From a historical point of view, the characterisation of science in relation to its method can be divided into four well-differentiated phases: two first phases defined by the pursuit of the unique and genuine scientific method, a third phase characterised by an acute meta-methodological criticism and the subsequent "end of method", and a fourth phase of particularism and discipline-specific scientific methods (Chalmers, 2013; Andersen and Hepburn, 2015):

- **Phase 1:** It extends from Plato up until the 17th century. This phase is characterised by conceptualisations of the scientific method that are strongly reliant on logic. Starting with Plato and his emphasis on deductive reasoning as the way to attain knowledge, probably the most influential contribution of this period is that of Aristotle and his systematic treatise on the nature of scientific inquiry, which outlines observation and reasoning about the natural world as the proper route to seek scientific knowledge. More specifically, Aristotle's system is described in the

Organon, where he primarily divides reasoning into deductive and inductive –a division which persists to the present day– and then he introduces his inductive-deductive scientific method. So as to fully understand Aristotle's method, let us briefly review the implications of deductive and inductive reasoning:

Deduction consists in deriving logical consequences from a set of premises –axioms– known or assumed to be true, i.e., it moves from a universal to particulars. Note that the great strength of logical deduction is its truth-preserving character, which implies that if the premises are true, then the conclusion must be true. Recall, however, that the truth of the factual statements that constitute the premises cannot be established by appeal to logical deduction, i.e., logical deduction is not a source of new truths, it can only reveal what follows from the premises already at hand (Chalmers, 2013).

Induction implies moving from particular premises –statements that stem from a finite number of cases/empirical facts– to general conclusions, i.e., it moves from particulars to a universal; consequently, it does actually go beyond what is contained in the premises, thus not being it possible to logically deduce inductive laws from the propositions from which they were obtained. In this vein, it is important to note that even though the premises of an inductive argument cannot prove the veracity of the conclusion, they do provide some degree of support for it.

According to Aristotle's inductive-deductive method of science, a scientist would start by carefully observing a particular species, then she would induce a general definition to explain a universal nature, and subsequently, she would deductively demonstrate the consequences of that universal nature for the particular species (Groarke). Importantly, syllogisms –both inductive and deductive– were the common vehicle throughout the entire process, which illustrates the pivotal role of logic in the Aristotelian conception of science.

The prolific Aristotelian work provided the framework for a commentary tradition on the scientific method during the medieval period. More precisely, figures such as Albertus Magnus, Thomas Aquinas, Robert Grosseteste and William Ockham –among others–, all worked on the Aristotelian contribution to clarify and/or reframe different aspects such as the kind of knowledge that could be attained by observation and induction, the justification of inductive reasoning, the rules to correctly apply the Aristotelian scientific method in general and inductive reasoning in particular, etc.

- **Phase 2:** It extends from the 17th century up to the mid-19th century. This phase is characterised by the philosophical battle between Rationalism and Empiricism. Rationalists embraced a neo-Platonic approach according to which nature had an intrinsically logical structure; therefore, the criterion of truth had to be intellectual and deductive and not sensory. In particular, rationalists considered mathematical description and mechanical explanation to be the bedrocks of the scientific method. Among the most renowned representatives of rationalism are Descartes, Spinoza, Leibniz and Kant. On the empiricist side, everything starts with Sir Francis Bacon –traditionally called the father of the experimental philosophy– and his Baconian method, which considered exhaustive methodical observation of facts as the means of studying and interpreting nature. More specifically, Bacon argued that science could be based only upon inductive reasoning, devoted a great effort to the correction of the different sources of error related to the limitations of our senses, and highlighted the need for a sceptical approach to science. At a later time, Newton, inspired by Bacon's ideas, laid the foundations of inductivism in his *Princpia Mathematica* and *Opticks*. In the century after Newton, several authors developed and clarified the Newtonian method; nevertheless, the Newtonian approach encountered criticism as well, in particular, in relation to its overemphasis on observation. In this context is where we find Hume's problem of induction, i.e., the problem of justifying the inductive inference from the observed to the unobserved. Hume noted that all such inferences rely –directly or indirectly– on the rationally unfounded premise that the future will resemble the past (Duignan, 2013). The problem of the certainty of inductive inferences led to the canonical methodological debate of the 19th century, whose most renowned representatives are Whewell and Mill. Whewell believed that knowledge is the result of both ideal and empirical elements, and he therefore sought a middle-way between pure rationalism and ultra-empiricism. As a matter of fact, Whewell's scientific method consisted of the following phases: (i) fact collection, (ii) clarification of fundamental concepts, (iii) clear formulation of inductive explanatory hypotheses –this is where *a priori* ideas and the subjective play an important role–, and (iv) careful testing. On the other side of the debate, Mill proposed a much narrower view of inductivism. In particular, he claimed that induction was the essence of the scientific method, that genuine inferential knowledge must be obtained by observation and experience –being its validity justified by the use of simple enumerative induction– and that no *a priori* knowledge exists.

- **Phase 3:** It extends from the mid-19th century until the last decades of the 20th century. This period is characterised by the recognition of the fallibility of empirical knowledge and the subsequent change of focus from the scientific method in its own right to the means of testing and confirming theories. In addition, this phase coincided with an outstanding development of philosophy of science, which led to a sustained meta-methodological criticism.

The different approaches to theory testing and evidence-based adequacy assessment include constructionism (Carnap), operationalism (Bridgman), the hypothetico-deductive (H-D) method (Hempel, Popper), Bayesianism, frequentism and severe experimental testing (Mayo). From all those proposals, the H-D method –or falsificationism– has undoubtedly been the most influential one. Briefly put, it consists in proposing a hypothesis, deducing its possible consequences and rigorously and ruthlessly checking them against the results of observation and experiment. In this context, a test that runs contrary to the hypothesis' possible consequences is taken as a falsification, while a test whose output is in perfect coherence with the expected consequences is said to corroborate the hypothesis, never to prove it true. Therefore, for the falsificationist, induction does not play a major role in science. In particular, as general laws cannot be logically deduced from observational statements, falsificationism proposes to take the inverse approach and use observational statements to deductively falsify general theories. Consistently, from the falsificationist standpoint, a hypothesis will only be considered scientific if it is falsifiable, i.e., if there exists a logically possible observation inconsistent with it, which, if established as true, would falsify the hypothesis.

Notably, falsificationism considers theory to take precedence over observation, as observation presupposes theory and is guided by it. In opposition to inductivism, for which science starts with stark observation, for falsificationism science starts with problems, problems associated with the explanation of a given behaviour of the universe and that acquire their status of “problems” in the light of a given theory. The falsificationist recognises that both facts and theories are fallible and envisions scientific progress as attained by trial and error. More specifically, since the truth of universal laws cannot be deductively proved, but proving their falsity is indeed possible, falsifications are regarded as the motor of scientific progress, being the greatest breakthroughs held to occur as a result of the falsification of cautious conjectures –i.e., well-established theories that are considered unproblematic– or of the corroboration of bold conjectures –i.e., conjectures unlikely to be true in the light of the background knowledge of the time. Importantly, even though according to falsificationism a theory can never be proved true, it can be acclaimed to be the best available theory in the sense that it has withstood tests that falsified its predecessors, hence being clearly superior to them. In the same line of argument, the greater the number of hypotheses that are confronted by the real world, and the more speculative and falsifiable –i.e., specific and precise– those hypotheses are, the greater the chances of major advances in science.

As regards the meta-methodological criticism that took place in this third phase, worthy of special mention are the contributions by Kuhn, Lakatos and Feyerabend, together with the insights by the sociologists of science from the 1970s onwards. As far as Kuhn, Lakatos and Feyerabend are concerned, the three authors considered that inductivist and falsificationist approaches were highly fragmentary and advocated for a more comprehensive account of science aimed at understanding the theoretical frameworks in which science takes place. Such an approach was inspired by a thorough exploration of the history of science and the realisation that to comprehend the development of major scientific theories, instead of focusing on the relationship between theories and individual observation statements, it was necessary to adopt a more global perspective and to look at scientific theories as structures.

Kuhn’s stance is structured around the idea that scientific progress has a revolutionary nature, being a revolution understood as the abandonment of a theoretical paradigm and its replacement by another incompatible paradigm. (Note that under paradigm, he refers to the general theoretical assumptions, laws and rules for their application, as well as the experimental techniques that the members of a certain scientific community accept as valid). Remarkably, Kuhn considered rival paradigms to be incommensurable in the sense that there exists no objective criterion to judge their merit. Consequently, he held that a change of paradigm was analogous to a religious conversion and compared scientific revolutions with political revolutions. According to Kuhn, the sequence of scientific progress would be the following: pre-science, normal science, crisis, revolution, new normal science, new crisis. In the normal science period, science is governed by a single paradigm of which normal scientists are uncritical, since otherwise –that is, if the fundamentals of a theory are constantly brought into question– no scientific progress can be attained. As far as crises are concerned, a crisis occurs when the number of problems that cannot be solved within a given paradigm –anomalies– becomes significant enough so as to pose a serious threat to the paradigm. When this occurs, a revolution takes place and the cycle starts again.

As regards Lakatos' contribution, it integrates key aspects of falsificationism with some of Kuhn's ideas while totally rejecting his relativism –the paradigm incomparability. Like Kuhn, Lakatos conceived scientific activity as taking place within a framework, what he called 'research program', which was, in a sense, his alternative to Kuhn's paradigms. According to Lakatos, research programs consist of a *hard core* –some very general hypotheses that constitute the basis from which the program is developed– and a *protective belt* –additional hypotheses whose role consists in complementing the hard core and protecting it from falsification, as any inconsistency in the match between a research program and observation is to be attributed to the supplementary assumptions of the protective belt. As for the comparison of research programs, the non-relativist criteria that Lakatos proposed states that a program is superior to another insofar it is more successful at predicting novel phenomena.

On his part, Feyerabend proposed an anarchistic theory of science which postulates that there is no scientific method. He sustained that any methodological constraint would only stifle scientific progress, and hence his approach is typically summarised under the principle "anything goes". It is important to note, however, that Feyerabend's plea against method is indeed a case against the claim that there exists a universal, ahistorical scientific method that contains the standards that all disciplines should comply with to be considered science. Remarkably, Feyerabend's stance, although controversial, has been very influential. Recall, for instance, that the currently widely accepted view that methods and standards in science are discipline specific and continuously evolving and changing for the better, is, in fact, a middle way between the existence of a universal method and no method at all, an intermediate position which was undoubtedly inspired by Feyerabend's seminal work.

Lastly, the criticism of sociologists of science regarding the scientific method was related to the social dimensions of knowledge. More specifically, they claimed that social ideologies (macro-scale) and interactions and individual circumstances (micro-scale) were the primary causal factors in determining which theories are worthy of the status of scientific knowledge.

Despite this period being characterised by the criticism of method and the acknowledged fallibility of both theory and experiment, during this third phase important progress was also made on statistical methods for hypothesis testing, i.e., on understanding how observation and experimentation can provide evidence for a given theory. Notably, both statisticians and philosophers of science engaged in substantial debates on the ultimate goal of hypothesis testing, being particularly famous the controversy between Fisher on the one side and Neyman and Pearson on the other. On Fisher's view, hypothesis testing is a rigorous methodology to determine when to reject a statistical hypothesis by evidence –namely when assuming that the hypothesis is true, evidence would be unlikely relative to other possible outcomes. Fisher's goal was a theory of inductive statistical inference that would provide a numerical expression of the degree of confidence in the tested hypothesis. In contrast, in Neyman and Pearson's view, the consequences of error should also be taken into account when deciding between hypotheses; more precisely, they introduced the distinction between type I error –rejecting a true hypothesis– and type II error –failing to reject a false hypothesis– and stated that one should compromise between committing type I or type II error on grounds of the consequences of those errors. More recent discussions on statistical inference have largely focused on Bayesianism –for which probability is a measure of the scientist's degree of belief in an event given the available information, her background knowledge and incoming evidence– and frequentism –which understands probability as a long-run frequency of a repeatable event. Both views have developed over time and continue to be both influential and widely discussed.

Because all the above, by the end of the 20th century, the idea of a single, universal scientific method had been ostensibly downplayed and abandoned in favour of an alternative conceptualisation of method as detailed and context specific problem-solving procedures. Notwithstanding, many of the ideas presented throughout this phase remain in force in our present-day practice of science.

- **Phase 4:** It extends from the close of the 20th century up to the present day. As previously suggested, this period is characterised by the embracement of pluralism, i.e., the acknowledgment that different discipline-specific and contextually limited scientific methods exist, and by a major focus on practice.

  Some of this phase's most influential views include: (i) Nersessian's notions that concepts are built by systematic reasoning as solutions to specific problems –problem-solving nature of science–, and her emphasis on the utility of model-based reasoning to overcome potential sources of error through cycles of construction, simulation, evaluation and adaptation of models; (ii) the different applications of experimentation beyond that of hypothesis testing –recall that one of the legacies of the third phase was the view that the main role of experiments is to test hypotheses according to the H-D method; nevertheless, the potential of experiments is much greater, being of particular interest what is known as 'exploratory experimentation', i.e., conducting experiments with the aim of identifying empirical regularities and/or to develop conceptualisations that describe/explain those regularities; (iii) the idea that theory-driven experimentation and exploratory experimentation are not opposite poles; quite the contrary, they are in fact complementary, as theory-driven experiments may also be directed at fact/data gathering and exploratory experiments are normally informed by theory; and (iv) the conceptualisation of computer methods as the third way of doing science –note that theoretical reasoning (deduction) and evidence-based induction are the first two ways; on the one side, computers are extremely useful to conduct experiments in the traditional sense, as they allow to efficiently process vast amounts of data at an unprecedented scale; on the other, computers, by modelling and simulation, constitute a new form of experimentation themselves.

After such a thorough examination of the notion and role of the scientific method throughout the history of science, we can confidently assert that at present, we find ourselves in a scientific context characterised by a particularistic approach to method and a major interest in computational developments and the ICT. In this regard, it is important to highlight that even though the particularities of each scientific field render its method discipline-specific, at a higher level of abstraction all scientific methods share some common principles such as objectivity, systematic nature, reproducibility, replicability and falsiability. Remarkably, in spite of the above-mentioned discipline-specific approach to method, there exists at the same time a marked interest in the development of cross-sectional tools, techniques and/or methodologies.

Consistent with the above, we shall now proceed to explore the scientific method of the Complex Systems field. Notably, it may be better thought of as a set of tools, some of which are discipline-specific –i.e., they have been explicitly developed to analyse phenomena that are characteristic of complex systems–, while the rest are general-purpose analytical frameworks and/or tools –i.e., tools that are used across many different disciplines such as statistical methods, machine learning tools, different modelling paradigms, etc.

To explore what may be termed the ‘complex systems analysis toolbox’, let us go from the general to the particular, that is, we will start covering the more general analytical approaches and techniques to end up with the more specific tools. Concretely, we first explore modelling as a scientific tool and some of the most common modelling purposes –both from a generalistic perspective and from the perspective of complex systems–, to subsequently move into the ABM paradigm, the Network Science discipline and the different Machine Learning approaches and techniques.

2.3 MODELLING AS A SCIENTIFIC TOOL

According to Epstein (2008), everyone is a modeller; in fact, in our everyday life, when we venture a projection and/or imagine how the dynamics of a given system would unfold, we are actually running a model, typically an implicit one –i.e., a model with hidden assumptions, untested internal consistency, unknown logical consequences and unknown relation to data– but a model after all. Consequently, as Epstein put it, the choice is not whether to build models; it is whether to build explicit ones.

In the scientific domain, renowned philosophers of science such as Hesse (1963) and Hughes (1997) claimed that it is by building and using scientific models that we improve our knowledge of the real systems observed, thus advancing science. According to Izquierdo et al. (2008), should we embrace a very broad and vague definition of model, then everything in science can be regarded as a model. From this point of view, model building constitutes the best and only way to improve our knowledge of the universe. Even though such an assertion may seem a categorical statement, the truth is that models are used across all scientific disciplines and at all levels of resolution.

In a general and simplified manner, the modelling process may be outlined around three main phases (Izquierdo et al., 2008): (i) abstraction, (ii) inference and (iii) analysis, interpretation and application of the results obtained (Fig. 2).

- **Abstraction.** The abstraction process is aimed at capturing the essence of the phenomenon under consideration. To that end, the modeller will have to disregard all accessory aspects that are irrelevant for the model's purpose, as it is by reducing the problem's original complexity that it is possible to undertake inference processes that would be unapproachable without the model.

  This phase generally begins with the observation of the real system and some data gathering. Subsequently, the modeller identifies clearly and unambiguously the system's components, the critical variables of the phenomenon under scrutiny, and the interrelations and interactions between both variables and the system's components. Eventually, the output of the abstraction phase, that is, the model of the target system, is obtained.

- **Inference.** In modelling, the inferential process consists in deducing the logical propositions that necessarily follow from the axioms and rules that define the model. Once the resulting logical propositions are obtained, they can be analysed, interpreted and applied to the real system.
- **Analysis, interpretation and application of the model's results.** The analysis of the results obtained is essential to understand the inner workings of the model. To that end, different mathematical approximations and/or statistical tools and methods are typically used. The immediate aftermath of the results' analysis is their interpretation, i.e., the determination of their meaning. Eventually, the last step of the modelling exercise consists in applying the knowledge obtained from our abstract model to the real system. Recall that such application may be either specific and concrete or tentative and approximate, being both scenarios potentially useful. In this vein, it is noteworthy that even though the model's conclusions will not rigorously describe what happens in the real system, they will provide, at the very least, a significantly better knowledge than it could be attained without the model.

In a nutshell, a model will be useful as long as it successfully captures the essence of the object of study, enables conducting inference processes that would be unfeasible without the model, and/or provides knowledge that is potentially transferable to the study of other problems/situations.

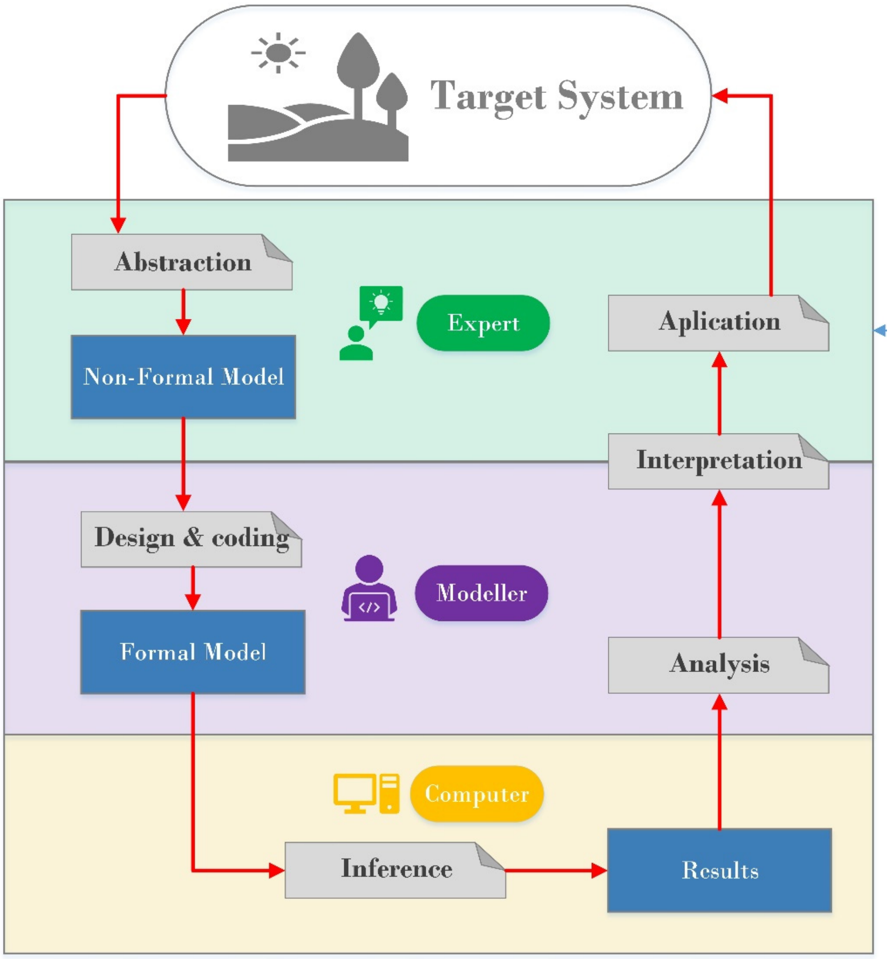

Fig. 2. Modeling process with intermediate abstraction, adapted from (Izquierdo et al., 2008; Galán et al., 2013). The figure shows a sequential scheme for clarity, but the modeling process typically contains several feedback loops.

Notably, even though the modelling exercise has just been described as a sequential process, as a matter of fact such process is rarely unidirectional; quite the opposite, it is generally non-linear and markedly dynamic, involving several feedback loops. Typically, the modeller creates a first preliminary model, explores the results it provides, and then she changes or adjusts the different assumptions as needed. More specifically, the assessment of the adequacy of the results consists of two well-differentiated processes: *verification* and *validation*.

Verification is the process aimed at determining if the model is correct, that is, if it works as intended by its designers. Thus, verification can be regarded as the process of looking for errors, i.e., mismatches between the design specifications and what the model actually is (Galán et al., 2009, 2013). Recall that even though the verification process is always necessary, it becomes even more important in the context of formal models, since the implementation of the model in a formal language and the logical derivation of the results are both particularly error prone.

Validation is the process of assessing how useful a model is for its intended purpose; therefore, in contrast to verification, validation does imply the comparison of the model's dynamics and/or results with the real system. Importantly, the model's utility is always determined in relation to both its design criteria (model's purpose) and its context of application (Izquierdo et al., 2008; Galán et al., 2013). These ideas happen to be key and thus will be covered in more detail in the next section.

Having reviewed the modelling process, it is time to explore the different modelling purposes; to that end, we will start with a general overview structured around Epstein's 17 modelling purposes (Epstein, 2008), and then we will focus on the most common modelling goals when dealing with complex social phenomena as covered by Edmonds et al. (2019).

DIFFERENT MODELLING PURPOSES

Epstein's 17 modelling purposes (Epstein, 2008)

1. Prediction.
2. Explanation.
3. Guide data collection. Even though it is commonly assumed that models derive from data and summarise them, in reality models and theories often precede data gathering, since in the absence of theory it is not always clear what data to collect.
4. Illuminate core dynamics. In this regard, it is important to highlight that even if all the best models are wrong –in the sense that they do not faithfully reproduce reality–, their capacity to capture qualitative/quantitative behaviours of overarching interest may turn them into invaluable illuminating abstractions.
5. Suggest dynamical analogies.
6. Discover new questions. Recall that it is the new questions that produce huge advances, and that models can help us discover new ones.
7. Promote a scientific habit of mind. As a matter of fact, Epstein regards this seventh purpose as the deepest contribution of the modelling enterprise. In particular, modelling enforces habits of mind essential to freedom, such as an iron commitment to "I don't know" and the arch-known "freedom to doubt". Therefore, modelling is a helpful tool to teach and disseminate the key features of scientific knowledge, namely that it is uncertain, contingent, subject to revision and falsifiable in principle.
8. Bound outcomes to plausible ranges.
9. Illuminate core uncertainties.
10. Offer crisis options/solutions in near-real time.
11. Demonstrate trade-offs and/or suggest efficiencies.
12. Challenge the robustness of prevailing theory through perturbations.
13. Prove the incompatibility of prevailing knowledge with available data.
14. Train practitioners.

15. Discipline the policy dialogue about options.
16. Educate the general public (educational models).
17. Reveal the apparently simple (complex) to be complex (simple).

MODELLING PURPOSES TO EXPLORE COMPLEX SOCIAL PHENOMENA

Given that the present thesis is devoted to the analysis of ethnographic, anthropological and archaeological data, it is appropriate to analyse in a little more detail the prevalent modelling goals within the Social Sciences and the Humanities. To do so, we will follow the analysis in Edmonds et al. (2019), which is particularly focused on the possible purposes for simulation models of complex social phenomena, but which is also enlightening for other model types.

Remarkably, Edmonds et al. (2019) start by making a number of key clarifications with regard to the modelling enterprise, namely:

- The importance of the model's purpose and of making it clear. In this regard, it should be noted that systems are not modelled per se, but for a particular purpose, being that purpose what determines which elements are important and should be included in the model and which not. Accordingly, the goodness of the model has to be assessed against how useful it is for its declared purpose, as different modelling purposes imply very different ways of building, checking, justifying and judging models.

  In this vein, it is also noteworthy that even though a model conceived for a purpose may be used for another purpose, it will need to be re-justified for the new purpose –and probably re-checked, re-validated and even re-built in a different form.
- The power of formal modelling lies in turning an implicit model into an explicit one, i.e., in transforming the initial informal set of ideas into explicit assumptions and mechanisms that are unambiguously expressed in the form of code or mathematical expressions. Notably, the resulting lack of ambiguity is of paramount importance for the scientific enterprise, as it facilitates the rigorous assessment of the model's assumptions and its consequences, avoids transmission errors, and thereupon fosters discussion, critique and the improvement of the model.
- The great variety of reasons for building a model, together with the prevailing misconception of modelling as a correspondence picture –i.e., the idea that the details of the model correspond with those in the real system in a roughly one-one manner–, result in a great potential for confusion. Recall that the picture analogy does not hold in most cases, since as models are built for a given purpose, the results obtained, their interpretation and their applicability will be restricted to a well-defined set of conditions of application.

The main reasons for modelling in the field of social simulation as identified by Edmonds et al. (2019) include: (i) prediction, (ii) explanation, (iii) description, (iv) theoretical exploration, (v) illustration, (vi) analogy and (vii) social learning. As the authors noted, there will be other modelling purposes that are not covered in the former list. Nevertheless, this is not a problem since their aim –and ours– is not to provide an exhaustive list of all the different modelling goals in the context of complex social systems, but to focus on the main ones and their practical implications. In particular, here we will just focus on their main characteristics, potential risks and some advisable mitigating measures.

PREDICTION

Definitions and key clarifications

- The definition of the term 'prediction' is not uncontested in the literature (Hassan et al., 2013). In fact, it has at least two different meanings: (i) it is used to designate the inference of a certain output from available data and/or from a set of assumptions via computation; and (ii) it is also used in reference to reliably anticipating unknown data. In an attempt to distinguish between the two alternatives, some authors decided to use the term 'forecasting' for the anticipation of unknown results; however, others started using prediction and forecasting interchangeably, thence contributing again to increase confusion. For all the above, every time we use the word prediction, it is necessary to clarify how we define it.
- In Edmonds et al. (2019) prediction is used in reference to reliably anticipating anything that is not currently known –and that can be unambiguously checked after it is known– to a useful degree of accuracy. In this definition: (i) reliably implies that if the model is used following its explicit application conditions, it will work; (ii) not currently known emphasises that for a predictive model to be successful, it has to predict well on data unknown to the modeller; and (iii) to a useful degree of accuracy is closely related to the purpose of the model, as the required accuracy will vary greatly depending on the model's goal, its application context and the nature –quantitative or qualitative– of the output.
- Remarkably, the usefulness of prediction in Edmonds' et al. sense –i.e., in the sense of anticipating anything not known beforehand– is undeniable, regardless of whether it is a black-box predictive model providing no knowledge at all of its internal dynamics, or a faithful representation of the real system that is straightforwardly interpretable. In actual fact, prediction in this sense is considered a gold standard of science, being the ability to predict taken as the most reliable indicator of a model's truth.

Potential risks

- Prediction of unknown data is very hard for any complex social system; hence, it is rarely attempted. Notably, it is so difficult and failure-prone, amongst other things, for three main reasons specific to the Social Sciences, namely: (i) that the processes that should be included in the model are not always known –it is often the case that not considered processes, if included, would significantly change the results; (ii) a lack of enough data on multiple independent cases to assess the model; and (iii) available data not being of the right kind –e.g., data that is just a proxy of the phenomenon under study, thus being it necessary to make some strong assumptions; or data dominated by noise rather than information.

- Conditions of application being not clearly specified. After building a predictive model, it is essential to indicate the conditions under which the model predicts well; otherwise, it is difficult to apply it to new situations, as one does not know when the model can be relied upon for a prediction.

Recommended mitigating measures (to ensure that the model does indeed predict well)

- Test the model on several independent cases and make sure it successfully predicts unknown data before making assertions about its predictive power.
- Write a detailed user guide covering –at least– the following aspects: the declared purpose of the model, the conditions of application –i.e., the circumstances and assumptions under which the model is designed to operate–, the degree of accuracy attainable, and additional caveats worthy of mention.
- Make the model's code publicly available so that other researchers can explore it.

EXPLANATION

Definition and key clarifications

- Explanatory models are aimed at understanding why something occurs. In the context of simulations, explanatory models allow to establish causal relations from a given set-up –the assumptions and mechanisms of the model– to its consequences –typically measurements of the outcomes of the simulation. More precisely, the possible causal relations are the set of inferences/computations made as part of running the model –note that in the case of stochastic models, those causal relations will provide either a possibilistic explanation (A could cause B) or a probabilistic one (A causes a distribution of events around B which may be summarised via statistics).
- In contrast to predictive models –whose usefulness is independent of the model's typology–, when seeking for explanation the structure of the model is indeed important, as it determines and limits what the explanation consists of. (Recall that by structure we refer to the model's assumptions, the mechanisms implemented, the parametrisation chosen, etc.).
- Typically, we have either good predictive models or good explanatory models but not both at the same time. Remarkably, when dealing with complex social phenomena, explanation is generally easier than prediction, although sometimes prediction comes first.
- The criteria to determine what is a good explanation is not as clear-cut as in the case of prediction. Consequently, the assessment of the goodness of an explanatory model is not a straightforward endeavour, being remarkably more error prone.

Potential risks

- Firstly, it should be recalled that a good fit to the target data does not guarantee a good explanatory power of the model, as our model could indeed be just a particular realisation of the phenomenon under consideration, thus having no generalisation potential at all.

- Secondly, a poor understanding of the model dynamics may result in the explanation attained being attributed to the wrong causes. More specifically –and most notably in the context of complex systems modelling–, the explanation could be in fact dependent upon some accessory assumption –i.e., an assumption that is not considered essential to the explanation, is not necessarily derived from the real system and that is arbitrarily chosen to ensure the functioning of the model; in such a scenario, the explanation obtained would be an artefact, that is, a significant finding caused by accessory assumptions in the model that are mistakenly deemed to be irrelevant (Galán et al., 2009).
- Thirdly, it may be the case that more than one explanation fits the target data. Thereupon, even if our model establishes one plausible explanation, it does not mean that it is the correct one or the only one.

<u>Recommended mitigating measures (to improve the quality and reliability of the explanation obtained)</u>

- State clearly the purpose of the model, i.e., the aspects of the target data that are being explained.
- Implement plausible simulation mechanisms, trying to avoid as much as possible the inclusion of assumptions/dynamics that have no real referent.
- Determine the conditions under which the explanation holds by conducting sensitivity analyses, executing multiple runs, adding noise and looking for artefacts. Recall that to detect artefacts, it is advisable to assess the robustness of the model's results to changes in the accessory assumptions, an assessment which should be conducted by taking one accessory assumption at a time.
- Make the model reproduce multiple patterns simultaneously, since each pattern will serve as a filter of unrealistic parameter values and/or dynamics, hence potentially avoiding artefacts.

DESCRIPTION

<u>Definition and key clarifications</u>

- When the purpose of a model is description, such a model is an attempt to represent the essence of a given observed case (or of a small set of closely related cases). Consequently, it is heavily reliant on data and seeks to fit evidence very closely. As a result, no generality beyond the cases under study can be assumed –i.e., no big claims will be derived from descriptive models.
- Descriptive models are currently somewhat under-appreciated. Nevertheless, they constitute very valuable tools, as they serve to formally record relevant aspects of the phenomena under consideration, and thus may be used to inform future research and/or to inspire higher-scale models.

Potential risks

- Descriptive models tend to be biased towards the inclusion of elements that are easier to represent, i.e., difficult aspects are less likely to be captured in descriptive models than easier ones.
- The model will be formulated in terms of the modeller's background knowledge, i.e., it will be the result of looking at the system of interest through the lens of the structures, mechanisms and programming languages that the modeller is familiar with. Therefore, a model is nothing but a particular abstraction of the phenomenon of interest that is expressed using a certain set of modelling tools. Note that even though the programming language, the accessory assumptions and the strictly technical implementation choices should ideally not influence the results, they may actually have an impact on them.
- Typically, a descriptive model does not include all the processes that exist in the real system; in fact, it is possible that it does not even include certain aspects that are indeed relevant.

Recommended mitigating measures

- Document thoroughly all the details of the model, that is: (i) the data, evidence or experience it is based upon; (ii) the selectivity embraced to choose the aspects to be included in the model; (iii) its acknowledged and possible biases; and (iv) the detail of the inference process. To that end, standards for documentation such as the ODD (Grimm et al., 2010) are very useful, as they help ensure that all aspects are duly covered.

THEORETICAL EXPOSITION

Definition and key clarifications

- The aim of theoretical exposition is to explore the theoretical properties of mathematically intractable models via simulation. More precisely, the focus of theoretical exposition is on the mechanisms and inner workings of the model, on how they interact and produce the different outcomes, thus being typically vaguely motivated with reference to observed phenomena.
- Specifically, theoretical exposition consists in establishing hypotheses about the general behaviour of a set of mechanisms and in subsequently characterising and/or testing those hypotheses via simulation. Recall that for the hypotheses to be useful, they need to be as general as possible. In addition, even though the establishment of hypotheses is of interest per se, the decisive utility of theoretical exposition is to be found in the refutation (or not) of those hypotheses by a well-designed sequence of simulation experiments. Eventually, theoretical exposition can also be used to look for artefacts, i.e., to assess the robustness of the results to changing certain assumptions of the model.

Potential risks

- Overinterpreting the results and extrapolating them to the real world. Note that even though the model might suggest a hypothesis about the observed phenomenon, it does not provide any empirical support for it.

Mitigating measures

First of all, it is important to note that the set of mitigating measures proposed here within the context of theoretical exposition are in fact applicable to all simulation models in general. Those recommendations are:

- When establishing hypotheses, be clear about their aim and scope.
- Document your code precisely and unambiguously. Consider using documentation standards such as the ODD and explain how the code relates to the theoretical assumptions.
- Make your code publicly available.
- Conduct a thorough check of your code.
- Perform sensitivity analyses by changing the initial conditions, adding noise, testing for extreme conditions, etc.
- Illustrate the simulation process so that readers understand its key dynamics.
- Provide a series of attempted refutations of the hypotheses to show their robustness.
- Be cautious not to make general claims about the real world by extrapolating the hypotheses of your theoretical exposition model.

ILLUSTRATION

Definition and key clarifications

- Illustration is the instantiation of a set of ideas in a formal structure that can be indefinitely explored and critiqued. It is typically used to exemplify and/or clarify an idea, theory or explanation.
- An illustrative model does not have to comprehensively represent the phenomenon it is representing. As a matter of fact, illustrations are generally simplified examples; therefore, illustrations should not be relied upon for inference processes.
- One of the most influential uses of illustration is as a counterexample to a certain assumption/theory.

Potential risks

- An illustration is typically tested for a restricted set of possibilities; therefore, the scope applicability of its results are markedly limited.

Mitigating measures

- Be clear that the purpose of the model is for illustration only and provide a detailed explanation of the idea that is being illustrated and how it relates to a given theory, a particular assumption, etc.

ANALOGY

Definition and key clarifications

- Analogical thinking consists in applying ideas, structures or models from one domain to another. It is typically used to provide new insights into well-known problems and/or as a guide to explore unfamiliar phenomena.
- Notably, analogical models lack a direct relationship between the analogy and empirical evidence; the relation between the two is just indirect, being it established through the modeller's intuitive reasoning.
- Analogical thinking is a very valuable scientific tool, as it helps to shed light on unknown phenomena, provides new perspectives and offers new examples for consideration. Nevertheless, its utility is restricted to the above-mentioned possibilities, being it not adequate for further purposes.

Potential risks

- Being able to think of a given phenomenon using a particular notion/structure/framework should not be confused with the veracity or adequacy of such an approach. In fact, analogies are not firm foundations from which inferences can be safely made. Thereupon, the main risk is to consider that a certain idea has explanatory or predictive power just because we can apply it to the system that we are interested in.

Mitigating measures

- When a model is used as an analogy, it is of paramount importance to state clearly that its purpose is limited to offering new perspectives of the problem at hand, and that no rigorous relationship with evidence is intended. This way we will prevent future users of the model from deriving erroneous inferences.

SOCIAL LEARNING

Definition and key clarifications

- Models whose purpose is social learning are built collectively by a group of people in the pursuit of an optimal or trade-off solution to a complex problem. More specifically, in this context, building a model collaboratively implies –among other things–: (i) generating a set of information that is shared among participants, (ii) creating a common knowledge/understanding of the problem, (iii) exploring common goals from different perspectives, and (iv) understanding the different views and interests of the parties involved. As a result, the knowledge of all members is increased, and the model obtained may act as a mediator -thus avoiding the misunderstandings that typically result from more abstract discussion-.

Potential risks

- The choice of adequate tools is crucial, since simple tools may be discarded by policymakers, while extremely sophisticated ones may prevent laid people from taking active part in the project. In addition, it is necessary to find a trade-off between selecting a generic approach and lowering the resolution level to include certain particularities; recall that if the model is too abstract it may not capture the interest of participants concerned by real-life problems, whilst if it is too specific it may not be significantly useful either.
- In the context of participatory modelling processes, there is a danger that the models are used to favour the interests of a particular subset of stakeholders over others.

Mitigating measures

- Modellers and designers should explicit the objectives and assumptions considered at all times, so that the different stakeholders can make informed decisions as to whether to accept or reject them.

MODELLING STRATEGIES

A modelling strategy is a general guideline that may be used to develop a model and to check it afterwards. Noteworthily, no modelling strategy is right, wrong or better than others in every case, it is simply more or less helpful for the context and purpose at hand. Some of the most renowned modelling strategies include (Edmonds et al., 2019):

- Keep It Simple Stupid (KISS). This strategy consists in starting with the simplest possible model and adding complication only when strictly necessary. Such an approach is a well-established principle in engineering since it maintains the maximum control and understanding of the model as it develops, thus reducing the chances of making mistakes. If this strategy had to be summarised in one sentence, that would be: "keep the model as simple as possible" (Axelrod, 1997).
- Minimise the Number of Parameters (MNP). This strategy is aimed at developing a model with as few parameters as possible in order to reduce the output space. Recall that under MNP, the model may have complex dynamics as long as the number of parameters is small.
- Minimise the Number of Free Parameters (MNFP). MNFP is a slight modification of MNP. In this case, it is the number of free parameters of the model -i.e., those that cannot be determined via measurement of the target system- that that is kept as small as possible.
- Keep it Descriptive Stupid (KIDS). This strategy starts the model exploration from the inclusion in the model of all the empirical evidence available. Subsequently, the modeller may try to simplify the model by removing certain aspects and checking if their elimination makes any significant different on the results (Edmonds and Moss, 2005).

- Make the Model More Like the Phenomena (MTMMLTP). In contrast to KIDS, which is strictly based on pure evidence, MTMMLTP aims at developing a model in accordance with how the modeller thinks things are, i.e., what is being modelled here is not evidence per se, but the interpretation the modeller makes of that evidence.
- Enhancing the Realism of Simulation (EROS). This strategy may be considered a sub-case of MTMMLTP, since it calls for expanding the cognitive models used in simulations to be more psychologically plausible. To that end, typically some aspects of certain psychological theories are included in the model.
- Keep It a Learning Tool (KILT). This strategy is specifically conceived for the purpose of social learning, as it aims at maximising the model's relevance and accessibility so that participants engage in specifying and/or improving it.

COMPUTATIONAL MODELLING OF COMPLEX SYSTEMS

In the previous sections, we have gone from the general to the particular to explore different aspects of modelling. More specifically, we started by depicting a very general scheme of the modelling process, then we dealt with the different modelling purposes, and ultimately we focused on the prevailing modelling goals within the complex systems field, and on some of the modelling strategies that may be used to attain such goals. Recall that the focus was turned upon complex systems since, as previously stated, all the phenomena explored in this thesis fall within the category of complex systems. Notably, given the characteristics of complex systems -decentralised nature, self-organisation, different hierarchical levels presenting inter- and intra-level interactions, emergent phenomena, adaptation, non-linear feedback and causality loops-, the modelling process of complex systems deviates somewhat from the general modelling process described above, as it requires more layers. Therefore, in this section we present the stages that the modelling process of complex systems consists of in accordance with Izquierdo et al. (2008).

Before delving into the specifics of the modelling process of complex systems, let us clarify certain ideas:

- The nature of complex systems makes it significantly difficult -or even impossible- to develop formal models that are both an adequate description of the system at hand and mathematically tractable. In fact, most models of complex systems are mathematically intractable, which implies that they can only be explored and analysed by means of computational models and simulations.
- Computational models –as their name may suggest– are models implemented in some programming language so that they can be run on a computer. As noted by Izquierdo et al. (2008), a model that is implemented on a computer and that can be run on it is necessarily formal. Therefore, both mathematical and computational models are formal, being the only difference between the two that they are expressed in different languages. Actually, every computational model can be expressed in mathematical language, although the equations obtained will be decidedly complex and potentially unsolvable.

- A formal model –be it mathematical or computational– can be thought of as constituted by a set of axioms –i.e., propositions admitted to be true– plus a set of inference rules; it is precisely through the application of those inference rules that new propositions can be deduced from the axioms and/or other previously inferred propositions. Note that since running a computational model implies logically deducing the results by applying the algorithmic rules of the model to the initial parametrisation, a computational simulation indeed establishes a sufficiency theorem: *R* -results- if *I* -initial conditions and algorithmic rules- (Axtell, 2000).
- When modelling in general, and even more so in the case of complex systems, the formal model is rarely based directly on the real system. Typically, a non-formal intermediate abstraction is made, being the final formal model built upon it. Noteworthily, such intermediate abstraction is generally incomplete and unfortunately it is not usually made explicit.
- As pointed by Izquierdo et al. (2008), to understand the modelling process of complex systems it is helpful to distinguish between three different roles: *expert*, *modeller* and *computer*. The expert is the specialist in the field of study, thus having a vast knowledge of the real system and its dynamics. The modeller is who designs, implements and analyses the formal model; therefore, she must be well-acquainted with formalisation procedures and programming languages. Eventually, the computer –i.e., the machine– is in charge of deducing the logical implications that derive from the initial conditions and the model premises.

EXPANDED MODELLING PROCESS FOR COMPLEX SYSTEMS

After presenting the three different roles, here we proceed to explain the different stages of the modelling process of complex systems, while indicating which roles are involved in each of them.

- **Abstraction.** The abstraction stage is the first phase of the modelling process. In it, the expert defines the objectives of the model, identifies the most important components of the system in relation to the model's intended purpose, and describes the most significant interactions and causal relations between them, all this in a clear and unequivocal way.

  As commented in the clarifications section, the model developed by the expert is typically non-formal. More precisely, it is generally expressed in natural language, it may include block diagrams to help explain the details of the interactions between the different components, and it may present some of the following flaws: lack of internal logical consistency, vague definition of certain concepts, use of ambiguous terms and/or incompleteness.

- **Model design and codification.** In this second stage, the modeller is in charge of designing and implementing a formal model based on the expert's abstraction. Thereupon, depending on the particulars of such abstraction it may entail different challenges; typically, the most frequent challenges are:

(i) *The expert's model is not fully specified*. This scenario, which is far more frequent than is thought, is characterised by the existence of a multitude of formal models that satisfy the expert's specifications. Recall that when different implementation alternatives satisfy a given premise of the expert, even though all these alternatives are equally valid in principle, they will presumably produce different results, thus being the choice between them not trivial at all.

(ii) *The expert's model lacks internal coherence*. Given that the expert's abstraction is typically expressed in natural language, this second challenge is also markedly recurrent. Remarkably, detecting logical inconsistencies in non-formal models is not straightforward either.

All in all, the modeller will have to design and implement a formal model –or a set of formal models– such that (i) each of those models is a valid instantiation of the expert's specifications, and (ii) that if a set of different implementations is presented, the complementary insights provided by all of them serve to reach a more comprehensive understanding of the problem under study.

Recall that throughout this entire stage, the modeller should ideally be in permanent contact with the expert, as she will need to clarify several assumptions and/or to agree on the choice of others. Notably, three main types of assumptions will have to be dealt with: (i) assumptions necessary to fully specify the model –e.g., particularisations of some general ideas expressed by the expert; (ii) assumptions related to computational capacity and/or pre-processing requirements so that the problem can be handled by a computer; and (iii) implicit assumptions related to the strictly technical implementation choices; note that sometimes not even the modeller is fully aware of these implicit assumptions.

Ultimately, once the formal model is fully designed and specified, the modeller will have to choose between different modelling formalisms, that is, between different alternatives to represent the same input-output relation. Typically, the choice is made between mathematical language and/or different programming languages. In this regard, should the implementation of the same formal model in different languages provide different results, such finding would be relevant in itself, as it would be pointing either to the existence of some kind of artefact or to a lack of robustness in the results.

- **Inference.** The inference stage consists in obtaining the propositions that logically derive from the model's axioms and inference rules. As previously noted, these results –logical implications– should be identical regardless of the modelling formalism chosen –which explains why the obtention of different results from different implementations of the same model is a scientific finding in its own right. In the case of mathematical models, the inference process may be conducted by a person that assumes the role of solving the model, while in the case of computational models, the inference process is always conducted by a computer.

- **Analysis.** Having obtained the model's results, it is necessary to analyse them in order to understand the functioning of the model. Remarkably, in models of complex systems the analysis of the results is not obvious, being it necessary to perform well-designed explorations of the parameter space and to make use of multiple analytical tools such as data visualisations, hypothesis testing, different statistical techniques, mean field approximations, etc. Recall that these analyses are generally conducted by the modeller, as they typically require some programming and data analysis skills.
- **Interpretation.** Once the results have been analysed, it is time to interpret their meaning in relation to the real system. To that end, the modeller and the expert will have to explore the results and their implications together, since it is only by integrating both perspectives that a successful interpretation will be attained. In addition, aside from the difficulties that such an interdisciplinary endeavour may entail, it should be recalled that in the context of complex systems the interpretation process is quite demanding per se, as not only the order of magnitude of the results is notably higher than in other model types, but also some of the results and/or the associated emergent phenomena are typically non-intuitive.
- **Application.** The ultimate goal of the modelling enterprise is the application of all the knowledge obtained from the modelled abstraction to the real system, a task that is typically performed by the expert. In this regard, it is important to note that the term application should not be understood in its strictest practical sense, since, on the one hand, the output of the formal model can be either extraordinarily precise –e.g. a numerical prediction– or exceedingly vague –e.g. the suggestion of a possible qualitative behaviour; and, on the other hand, all knowledge that can be derived both formally and unequivocally will necessarily refer to the formal model –neither to the first abstraction nor to the real system–, being thus its relation to the real problem more subtle and uncertain. Consequently, a strict interpretation of the results obtained may only be conducted within the framework of the formal model, as it is only in that context where the conclusions will be truly valid. Additional extrapolations to the first abstraction or to the real system will constitute mere suggestions of possible trends or behaviours.

Now that we have a clear idea of the different stages that the modelling process of complex systems consists of, hereunder we present what we have agreed to call *the complex systems analysis toolbox*, which contains some of the tools and analytical frameworks most commonly used to model and analyse complex systems, namely ABM, Network Science and Machine Learning tools –among others. Notably, after exposing the details of each tool/analytical framework we will explain how some of these techniques have been applied in the context of the present thesis, explanations that will hopefully serve as enlightening examples.

2.4 AGENT-BASED MODELLING (ABM)

ABM is a powerful modelling approach that has proved to be extremely useful for complex systems modelling in general, and for social systems modelling in particular (Izquierdo et al., 2008; Conte et al., 2012).

One of its distinctive traits is that it enables the creation of models that combine the descriptive richness of verbal models with the formal rigour of more abstract mathematical models. In particular, in ABM a system is modelled as a collection of heterogeneous, autonomous and independent decision-making agents who interact with their environment and/or with other agents in the pursuit of their own goals and objectives (Izquierdo et al., 2008).

The ABM paradigm implies a conceptualisation of complex systems as the result of individual actions and interactions, i.e., the system is described from the perspective of its constituents, being thus the basic components of the real system represented explicitly and individually. Consequently, ABM intends to infer the global properties of the whole system on the basis of a set of rules that determine the agent's individual behaviour –bottom-up approach–. Remarkably, modelling at the individual level entails the establishment of the following direct correspondences: (i) the entities in the real system correspond to the agents in the model; (ii) the interactions between them correspond to the interactions between the agents; and (iii) the boundaries defining the system's basic components correspond to the constraints defining the agents (Edmonds, 2001; Izquierdo et al., 2008). Thanks to those direct correspondences, ABM models present increased realism and potentially more scientific rigour than traditional approaches based on "representative agents". Notably, the ABM approximation presents a computational complexity that in most cases is mathematically intractable; consequently, the different dynamics are generally explored by means of computer simulations.

WHEN IS ABM USEFUL?

ABM is particularly suitable for modelling complex systems with the following characteristics (Epstein, 1999; Bonabeau, 2002; Izquierdo et al., 2008, 2016):

- *Heterogeneity*. Systems with heterogeneous individuals in contrast to representative individuals. Note that in ABM heterogeneous individuals are represented both explicitly and individually, thus providing a more faithful representation of reality, as individuals in the real world may actually differ in myriad ways –genetically, culturally, in terms of personal preferences, etc.
- *Autonomy*. In ABM the agents are fully autonomous in the sense that there are no central controllers –higher order authorities– governing their behaviour. In fact, each agent evaluates her situation and makes her own decisions following a predefined set of rules. Undoubtedly, there is feedback between the micro and macro levels, but ultimately decisions are made at the individual level.
- *Special interest in the micro-macro mapping*. ABM is particularly useful for the analysis of systems in which we seek to better understand the relationship between the micro-scale –characterised by the attributes and choices of the individuals– and

the macro-scale –the global properties of the system– (Squazzoni, 2008). More precisely, because of ABM's bottom-up approach, it is generally the tool of choice for the study of emergent phenomena, i.e., processes in which individual-level behaviour generates higher-order structures.

- *Explicit space*, i.e., systems in which the geographical/environmental setting may have a significant influence. Recall that ABM facilitates the representation –and hence the consideration– of the physical space across which the agents move and interact, thus allowing to assess its impact on the observed phenomena. In this regard, it is interesting to note that all other things being equal, different spatial configurations –an *n*-dimensional lattice, different social networks, etc.– may lead to different results.

- *Local and asymmetric information* in contrast to perfect information. Perfect information assumes the ideal scenario in which all agents have the same information, i.e., a complete and instantaneous knowledge of all other agent's actions. Such an idealisation is barely found in reality; in fact, many complex systems –and particularly socio-economic ones– present local and asymmetric information, which means that there exist individuals with different, more or more detailed information than others, i.e., not all agents have access to the same information.

- *Local interactions*. In real systems, homogeneous mixing is generally not the rule. Actually, agents typically interact with neighbours from their vicinity, and their relational patterns may be influenced by several factors. As far as ABM is concerned, it allows to explicitly include in the model complex topologies of interaction such as social networks, thus enabling a more accurate representation of real relations.

- *Complex interactions*, i.e., when the interactions between agents are nonlinear, discontinuous or discrete; recall that nonlinear and/or discontinuous interactions are usually related to triggers/thresholds, that is, the agents only respond/change their response pattern after a given threshold has been surpassed. Since describing discontinuities in individual behaviour is difficult with differential equations, ABM is the most suitable approximation in the face of complex interactions.

- *Path dependence and initial-condition dependence*. Path dependence refers to the attainment of a given state and/or long-run equilibrium as a result of past actions –historical effects. On its part, initial-condition dependence –as its name would suggest– makes reference to the dependence of simulation results on initial conditions. In this context, it is interesting to note that Markov processes modelling is an extremely valuable framework for the analysis of initial-condition dependence/independence.

- *Finite parameters and finite populations*. ABM models work with parameters that take finite values; consequently, instead of taking limits and working with infinite populations, ABM models operate with a finite number of agents.

- *Stochastic processes* as opposed to deterministic approaches. At this point it is necessary to clarify that by deterministic approaches we refer to those conceptualisations considering infinite populations, infinite time and conducting expected value analyses. Given that ABM approaches work on the basis of finite parameters –and hence finite time and finite populations–, and that their results are obtained via simulation, they constitute a very convenient option to model stochastic processes.

- *Adaptive systems*, i.e., systems including individual adaptation (learning) and/or population-level adaptation (evolution). Adaptation at individual level refers to a change in the agent's strategy to increase her chances of achieving her individual goals; it should be clarified that such a change will only lead to individual adaptation if it is maintained over time. On its part, adaptation at population level is linked to the concept of evolution and evolutionary systems, being thus related to selection, replacement and diversity mechanisms.
- Bounded rationality. The term *bounded rationality* was proposed by Herbert Simon (1957) as an alternative to the *global rationality* of traditional economic theory. Global rationality or hyperrationality sees decision-making as a fully rational process aimed at finding an optimal solution –maximising a given utility function– (Simon, 1955). Conversely, bounded rationality acknowledges that individuals are only partly rational, and that given the limitations inherent to the decision-making process –namely bounded information and bounded computing capacity of the individuals– they seek satisfactory solutions rather than optimal ones; typically, individuals choose an option that fulfils their adequacy criterion according to simple rules based on local information.

EMERGENCE AND GENERATIVISM

At this point, it is important to discuss one of the crucial points of ABM, namely the concept of *emergence*. Emergent phenomena can be succinctly defined as "stable macroscopic patterns arising from the local interaction of agents" (Epstein and Axtell, 1996). As noted by Izquierdo et al. (2008), the most characteristic aspect of emergent phenomena is that they are unanticipated, i.e., that they are not straightforwardly deducible from the specification of the individual behaviour and the interaction rules of the agents. Put another way, an emergent phenomenon is more than the sum of the systems' parts precisely because of the interactions between those parts; thereupon, it can have properties that are fully decoupled from the properties of each part, being thus counterintuitive in some cases and difficult to understand/predict (Bonabeau, 2002). Emergent phenomena abound in the real world and most notably in the Social Sciences. Archetypal examples of emergent phenomena include traffic jams, market dynamics, cooperative behaviours and the diffusion of innovation –to cite a few. Notably, in ABM approaches modelling the human ability to perceive, monitor and understand the macro-structures of the system they are part of –a capacity that is shared by some other animals such as primates (Dally et al., 2010; Horschler et al., 2020)–, we may identify not only *first-order emergent phenomena*, but also *second order emergent phenomena*, i.e., macroscopic regularities that originate when each agent becomes aware of the emergent phenomenon she is partially causing, and reacts changing her behaviour in response (Gilbert, 1995, 2002). Typical examples of second-order emergent phenomena can be found in the stock market, a context in which each agent may base her decisions on an individual model of the first-order emergent phenomenon at hand, thus existing a complex feedback loop between the macro-scale (the emergent phenomenon) and the micro-scale (the individual decisions).

Additionally, it is important to highlight that ABM simulation explicitly models the emergence process that leads from the behaviour and interactions of the individual components to the aggregate variables observed at the macro-scale. This fact constitutes a differential aspect of the ABM paradigm with respect to other modelling approaches; in system dynamics, for instance, the emergence process is presupposed a priori, and it is the different relationships between the system's variables –typically aggregate– that are explicitly modelled. As a consequence of the foregoing, ABM is the canonical approach to modelling emergent phenomena.

Deeply intertwined with the concept of emergence is the scientific trend known as *generativism*. The generativist is interested in the formation dynamics of emergent phenomena and seeks to understand them by identifying plausible generating mechanisms. The specific question they intend to answer could be formulated as follows: *How does a given macro-scale regularity emerge from the decentralised local interactions of heterogeneous autonomous agents?* Interestingly, they propose to embrace an ABM approach to answer that question, being their motto that "if you cannot grow it, you cannot explain its emergence" (Epstein, 1999). As a matter of fact, ABM models provide computational examples that a given micro-configuration suffices to generate a target macrostructure, i.e., that the emergent pattern is effectively attainable by repeatedly applying a particular set of individual agent-interaction rules. In the generativist realm, such a demonstration is actually held as a necessary condition for explanation. Nevertheless, the fact that a given micro-specification generates the macrostructure of interest does not imply that it is the only and true explanation of the emergent phenomenon at hand. Indeed, different micro-configurations may fit the macro-data equally satisfactorily, thus having equivalent generative power. Under those circumstances, each micro-specification constitutes a candidate explanation, being further micro-level empirical work required to determine which one of them is the most tenable.

ABM AND THE SCIENTIFIC METHOD

An important remark regarding generative approaches is related to their role and place within the scientific method. As Axelrod (1997) put it, simulation is a third way of doing science since it is neither strictly deductive nor purely inductive. Notably, even though every computation constitutes a logical deduction in the sense that it can be obtained from other –usually more general– propositions, and ABM systematically performs plenty of computations for each agent, the truth is that ABM is significantly different from strictly deductive science, as it does not prove theorems. On the other hand, ABM is not inductive in its traditional sense either, since even if simulation data can be analysed inductively, such data do not come directly from the real world –they are obtained from a rigorously specified set of rules instead. It is precisely for all these reasons that the distinguishing term *generative* was coined (Epstein, 1999), since, as a matter of fact, generative methods constitute a scientific instrument in their own right. More specifically, ABM is a powerful empirical research tool because it serves to formulate explicit hypothesis of the form *Does the micro-configuration under consideration suffice to generate -and subsequently explain- the pattern observed at the macro-scale?* The answer to such question can be affirmative, or, more interestingly, negative, the latter alternative allowing to falsify the proposed hypothesis. Remarkably, it is this falsification capability that turns ABM into a scientific instrument, as it allows to falsify hypothesis and/or theories in the traditional Popperian sense (Chalmers, 2013; Mauhe, 2019). From all the above, it becomes clear that ABM is useful as falsification tool and as a computational theorising methodology, serving also to guide future research by pointing to previously unexplored aspects/regions, inspiring new data collection, etc.

In addition, interdisciplinary research can also benefit from ABM modelling approaches, as they allow to transcend the boundaries between disciplines by integrating in the model diverse spheres of the problem –see for instance demography, climatology, economics, cultural evolution, etc.

Lastly, another relevant application of ABM is theory testing. In fact, ABM can be used to test the robustness of traditional standard theories to particular changes/relaxations in the assumptions. Typically, one relaxes assumptions on the micro-level behaviour to check if the emergent phenomenon at the macro-level remains unchanged and/or collapses. However, any assumption can, in principle, be modified to assess its impact on the results, and hence to determine if the observed phenomenon was an artefact or a robust trend.

CHALLENGES OF ABM

1. **Equations in ABM.** Are there equivalent equations for every computational model? Absolutely. The problem is that it is not always obvious how to formulate those equations, and even more so in ABM models.
2. **Exploration of the parameter space.** Given the magnitude of the parameter space in ABM models, it is necessary to sweep such parameter space in order to obtain a faithful statistical portrait of the relationships between inputs and outputs. Nevertheless, in the event of a space of possible agent behavioural rules, to this day, there is no prevailing method to efficiently search that space.
3. **Mathematical intractability and the need for sensitivity analyses.** The problems that are generally modelled by means of ABM are usually so complex that they are mathematically intractable. Consequently, computer simulation in general, and ABM in particular, constitute extremely valuable tools to gain insights into their dynamics. In this regard, sensitivity analysis allows to assess the effect on the output (the generated macrostructure) of a small change in the input (the micro-specification).
4. **Difficulty of model comparison.** Despite the enormous popularity of ABM to study complex systems coming from very different disciplines such as Biology, Sociology, Archaeology, Economy, etc., the truth is that as noted by Hales et al. (2003) ABM models are rarely compared on a model-to-model basis. Even though some of the

difficulties already pointed by Axtell et al. (1996), such as the lack of standards for model comparison and replication have already been overcome to some extent –see for instance the ODD documentation protocol (Grimm et al., 2010)–, to this day much work remains to be done regarding ABM model comparison (Grimm et al., 2020). Some of the most promising "open issues" include: (i) the integration of top-down with bottom-up models (i.e., equation-based models with ABM models); (ii) the establishment of structured methodologies for model alignment –comparing different models that claim to have similar results to check if they can actually produce the same results and/or one model can subsume another; (iii) the identification of potentially unifying phenomena by taking ABM models that explore different problems and assessing if their behaviour intersects; and (iv) fostering replication of ABM models as a worthwhile exercise to increase confidence on the veracity of results.

5. **Models specified differently that have essentially the same results.** This challenge is very closely related to the previous one. Under this scenario there is no single 'correct model', but a family of models that produce equally adequate results –from the point of view of intended interpretation. Traditionally, the choice among them has been conducted on pragmatic grounds, being the simplest model selected. However, despite its greater understandability and didactic value, the simplest model does not need to be the most correct and accurate one. Henceforth, further empirical validation and/or model alignment are needed to determine the model that best fits real data and/or to check if the different models at hand can be subsumed into one (Edmonds, 2001).

6. **Artefacts.** Artefacts are not legitimate results that can be created throughout the model's design, implementation and/or execution. Notwithstanding, it happens to be extremely challenging to detect which assumptions in the model are generating a given set of outputs, thus being the identification of artefacts really troublesome. In the next section we will cover some of the key aspects in relation to errors and artefacts. For a more thorough review on the topic please refer to (Galán et al., 2009).

ERRORS AND ARTEFACTS

ABM models are generally mathematically intractable, being thus computer simulation necessary for their exploration and analysis. Notwithstanding, computer simulations can indeed be very complex, hence being it neither easy nor straightforward to understand their intricacies in detail.

The enterprise of understanding a simulation consists in identifying which parts of the code are producing the different results, something that is not trivial at all. On top of that, when trying to identify those correspondences, we are faced with an additional problem, namely tracing the cause of an unexpected result; this is again quite problematic, since the unattended result could be either the consequence of an error or artefact created during the model conceptualisation, implementation and/or execution, or a truly unforeseen output of the model itself (Axelrod, 1997; Galán et al., 2009). Thereupon, once a model is built –and most notably in the case of ABM models–, the identification of both potential errors and artefacts is of paramount importance, since only after having systematically assessed and eliminated them will our results be reliable and robust.

Simulations require a vast array of diverse assumptions to be fully operational. This is not exclusive of ABM simulations; in fact, it is a common feature across all formal models. Nevertheless, it is worth stressing that the more complex the model, the more assumptions are made and the more intertwined they are. In the present thesis, we propose to follow the systematic model assessment procedure by Galán et al. (2009) to gain a better understanding of our models, and thus have greater confidence in our results. Such procedure is conceived to facilitate the comprehension of the different assumptions made, their role, how they accumulate to configure the entire model, and to identify the different stages of the modelling process where different errors and artefacts may occur. It is important to note that even though their proposal presents recommendations and rules of general applicability –valid for all modelling approaches–, it is particularly conceived and illustrated for ABM models.

At this point, it is necessary to clarify the meanings of *errors* and *artefacts*. *Errors* occur when the model does not comply with the agreed requirement specifications –i.e., there is a mismatch between what the model is intended to do and what it actually does; therefore, errors are frequent in the implementation stages –code bugs, unconscious use of floating-point arithmetic, etc. (Polhill et al., 2006). The process of looking for errors is known as *verification* and it always has to be conducted with regard to the model's intended purpose. As far as artefacts are concerned, they occur when there is an incongruity between the set of assumptions the modeller thinks that are producing a given phenomenon and the assumptions that are actually causing it. As noted by Galán et al. (2009), to better grasp this concept, it is necessary to differentiate between *core* and *accessory assumptions*. *Core assumptions* are those considered to be important for the purpose of the model; ideally these would be the only assumptions. Nevertheless, in practice, additional assumptions are generally required to make a model work; these extra assumptions are known as *accessory assumptions* and their only purpose is to ensure the operability of the model, being thus deemed uncritical for the model's goal. In this vein, it is also important to distinguish between *non-significant* and *significant* assumptions, the latter being the cause of a certain significant result of the model under consideration. Accordingly, artefacts can alternatively be defined as significant phenomena caused by accessory assumptions erroneously thought to be non-significant. The process of looking for artefacts is known as *validation*; however, it is worth noting that the relationship between artefacts and validation is not analogous to that between errors and verification, it is certainly more complex. In particular, artefacts are meaningful for validation as long as discovering and understanding causal/generative relations in the model's real referent is one of the aims of the modelling task. If this is the case, the existence of artefacts detrimentally affects the validity of the model, rendering it no-representative of its referent. Such non-representativity stems from the fact that in the presence of artefacts, one can change a given accessory assumption –remaining the core assumptions and the rest of accessory assumptions unchanged– and get significantly different results; i.e., the result thought to be significant is not a consequence of the core dynamics of the model but the incidental outgrowth of that accessory assumption.

For the sake of simplicity, from the exhaustive review in (Galán et al., 2009, 2013) of the different stages of the modelling process, the different actors involved –the thematician, the modeller, the computer scientist and the programmer– and the more error- and artefact-prone phases, we will just keep the key notions. In particular, from all the above-mentioned roles we will just focus on the modeller, the computer scientist and the programmer, with a special focus on the modeller and the computer scientist since they are the ones that can introduce the artefacts in the model. The modeller is the person in charge of formalising the thematician's abstraction –which is usually expressed in natural language– and it is precisely in the formalisation process that the first artefacts may be created, since typically a number of additional assumptions has to be made so that the formal model is fully specified. Regarding the computer scientist, her job consists in finding a computer-feasible implementation of the modeller's formal model; by computer-feasible we mean that the model can be run by present-day computers –in terms of memory, computing capacity, etc. To that end, the computer scientist might have to modify certain aspects of the modeller's formalisation –approximating or simplifying some elements for instance–, and she will be required to specify all the necessary information so that results are fully reproducible: the operating system, the programming language, the pseudo-random number generator chosen, and all other choices that could make a difference. As a consequence of all the above-mentioned decisions, the computer scientist has as well the potential of introducing artefacts in the model. Eventually, the programmer is the person in charge of actually writing the computer model in the programming language chosen; provided that the programmer makes no further/alternative decisions, she could only introduce implementation errors in the model.

Although in reality, different roles may correspond to the same person, as a matter of fact, the previous role categorisation and division of tasks is also useful to explain the various actions that can be taken at the different stages to avoid, detect and eliminate errors and artefacts.

At the **modeller level**, the most important recommended actions would include:

1. Keeping the core assumptions and implementing alternative accessory assumptions to check their impact on the observed results. Only those conclusions that remain unaltered across the different implementations will be valid.
2. Comprehensive exploration of the parameter space.
3. Creating mathematically tractable abstractions of the formal model -obtaining the model of the model- and/or of some of its parts, since it may be helpful to identify odd behaviours, incongruencies and/or subsections of the model where there may be conflictive assumptions/approximations.

At the **computer scientist** stage, the recommended activities are:

1. Developing mathematically tractable abstractions of particular cases to check them against the results obtained from the simulation.
2. Running the same code in different computers, with different operating systems, different pseudo-random number generators, different floating-point arithmetic systems, etc.

Eventually, the recommendations for the **programmer** would be:

1. Implementing the model in different programming languages.
2. Assessing the correct implementation of the model by checking it against extreme examples that are well understood and/or whose expected results are known beforehand (note that this is not always possible).

CURP MODEL

As regards the present thesis, one of the four articles constituting it is framed within the ABM paradigm, namely the one entitled “Robustness assessment of the ‘cooperation under resource pressure’ (CURP) model, Insights on resource availability and sharing practices among hunter-gatherers”. More precisely, this contribution takes the previously published ABM model by Pereda et al. (2017b) and evaluates the impact of changing the selection mechanism on the results. Before further delving into the details of such robustness assessment, let us briefly review the objective, assumptions, dynamics and results of the CURP model.

OBJECTIVE

The CURP model (Pereda et al., 2017b) was conceived to shed light into the emergence and evolution of cooperation in relation to resource availability among hunter-gatherer societies. In particular, it was inspired by plenty of ethnographic and archaeological examples pointing to the relevance of food sharing practices in the long-term survival and success of hunter-gatherer groups. More specifically, the main hypothesis it intends to test may be summarised as follows: *in hunter-gatherer societies with no food preservation technologies, a decrease in food resources would foster cooperation in the form of food sharing as long as reciprocity is plausible.* To assess the validity of such hypothesis, an ABM model belonging to the Evolutionary Game Theory framework was developed.

MODEL ASSUMPTIONS:

1. The size of the population is established to be equal to N people agents and remains constant throughout simulation.
2. Well-mixed population assumption: All agents can interact with all agents with equal probability at all times (no spatial structure is considered).
3. Events take place sequentially in discrete time periods, but no temporal scale is defined –i.e., time periods have no meaning in the sense that they have no real referent. The interest is in the asymptotic behaviour of the model.

4. People agents perform actions in random order and asynchronously to avoid first acting unintended consequences.
5. Resources provide a unit of energy to any agent who finds them.
6. Evolutionary assumptions. Recall that since the CURP model falls under the EGT framework, it is an evolutionary model. Notably, to be called evolutionary a model has to include the following three mechanisms: (1) selection, (2) replication and (3) mutation (Izquierdo et al., 2012).
   - *Selection*. Selection is the discriminating mechanism that favours some agents instead of others. In the CURP model selection is enacted in relation to fitness, i.e., agents with higher fitness are selected preferentially. More specifically, CURP's selection mechanism is random tournament, which is implemented as follows: a *strategy-tournament-size* sample is taken at random from the population and the strategy with the highest fitness is selected.
   - *Replication*. The replication procedure is in charge of preserving –either to a full or a certain extent– the agent's properties –or the agents themselves– from one generation to the next. In the context of the CURP model, the replication mechanism is imitation of the best strategy –the one with the highest fitness–. Note that selection and replication are very closely linked since –as Izquierdo et al. (2012) put it: *being selected* means *being selected to be preferentially replicated*.
   - *Mutation*. The mutation mechanism counteracts the reduction in diversity – homogenisation– that results from the joint operation of selection and replication. In CURP, the mutation process is modelled as follows: each agent randomly picks a strategy from the strategy space with *prob-mutation* probability.

STATE VARIABLES (VARIABLES THAT CHARACTERISE EACH AGENT):

- *Given-energy*: Proportion of the resource unit that an agent wills to share with other unlucky agents –those who did not get resources by themselves or from other donors. Recall that an agent always gives a *given-energy* proportion even if she eventually remains with less energy than the necessary for survival.
- *Correlation*: Parameter ranging from -1 to 1 that determines the probability of choosing a donee as follows:
  - Positive values → Represent the probability of choosing the most cooperative donee -the one with the highest *given-energy*- among all possible donees.
  - Negative values → The absolute value represents the probability of choosing the least cooperative donee -the one with the lowest *given-energy*- among all possible donees.
  - Otherwise the donee is chosen randomly.
- *Fitness*: Number of time periods in which the energy obtained by the agent was above the survival threshold –*min-energy*.

STUDY PARAMETERS (ENDOGENOUS VARIABLES WHOSE VALUES ARE ESTABLISHED BY THE USER TO DEFINE THE SIMULATION SCENARIO AND THAT REMAIN CONSTANT THROUGHOUT SIMULATION):

- *N-people*: Number of agents.
- *prob-resource*: Probability that an agent gets a unit of resource at each time period.
- *min-energy*: Survival threshold, i.e., the minimal proportion of the resource unit necessary for survival.
- *sharing-tournament-size*: Percentage of unlucky agents –those who did not get resources at the given time period– from which a particular donor will choose her donee.
- *strategy-tournament-size*: Percentage of the total number of agents in the population that a given agent considers in the imitation process.
- *prob-mutation*: Probability that an agent will follow a new strategy chosen at random from the strategy space.
- *rounds-per-generation*: Number of time periods after which agents can change their strategy (i.e., their *given-energy* and *correlation* parameters).

MODEL DYNAMICS

For rounds-per-generation time periods:

In each time period t:

1. Each agent gets a unit of resource with probability *prob-resource*.
2. Each successful agent –agent who did get a unit of resource– shares as follows:
    1. She takes a *sharing-tournament-size* sample from the pool of unlucky agents.
    2. She chooses a donee from the previous sample in accordance with her *correlation* value.
    3. She gives the donee a *given-energy* proportion of the resource.

Recall that once an unlucky agent receives more energy from other donors than the *min-energy* survival threshold, such agent will no longer be eligible.

3. Each agent updates her *fitness* increasing it in a unit if she has more energy than the survival threshold.

After *rounds-per-generation* time periods → Each agent updates her strategy as follows:

1. She takes a random sample of *strategy-tournament-size* from the population.
2. She imitates the best strategy –the one with the highest *fitness*- if the corresponding *fitness* is greater than her own.
3. With probability equal to *prob-mutation* the agent will randomly choose an alternative strategy from the strategy space.

RESULTS

The region of the model that was thoroughly analysed is that of asymptotic behaviour. To that end, the relative importance of the different study parameters in the configuration of the agents' strategies was determined by means of a random-forest-based variable importance analysis –for the details please refer to (Pereda et al., 2017b). Subsequently, the two most relevant parameters, namely *prob-resource* and *min-energy,* were evenly sampled to encompass a broad range of different scenarios of resource pressure; the rest of the parametrisation was set to arbitrary values and kept constant. The exploration of the results obtained led to the identification of three different stable regimes:

- *Low-stress regime* (high *prob-resource*, low *min-energy*): Scenarios in which survival is very likely and therefore most strategies are successful. Consequently, the selection mechanism plays almost no role in this region, being all the variability observed attributable to random drift. Recall that in this region the average strategic behaviour remains at almost constant values.
- *Intermediate-stress regime* (intermediate *prob-resource*, intermediate *min-energy*): Contexts in which the prevailing strategies consist in keeping the resources strictly necessary for survival and sharing the rest preferentially with those who were generous in the past. In this regime, cooperation and indirect reciprocity emerge so as to collectively lower the chances of falling below the survival threshold.
- *High-stress regime* (low *prob-resource*, high *min-energy*): Scenarios characterised by the struggle for survival. In this context, *low-given* strategies are favoured, being the agent's behaviour extremely fluctuating. In particular, since no strategy is satisfactory enough, the agents are constantly seeking new alternatives to ensure survival.

ROBUSTNESS ASSESSMENT OF THE CURP MODEL

In accordance with Galán et al. (2009), to increase our confidence in the results obtained with an ABM model, it is necessary to understand the simulations somewhat, at least to the extent that one can distinguish if the results were produced by core or accessory assumptions. To that end, they recommend implementing alternative accessory assumptions while keeping the core assumptions unchanged, an exercise which is extremely useful to detect artefacts.

As regards the CURP model, some of its most relevant accessory assumptions include: (i) the well-mixed population assumption, (ii) the asynchronous update of the agent's state variables, (iii) their acting in random order, and (iv) the specific selection, replication and mutation mechanisms implemented. As a matter of fact, all these accessory assumptions could have been checked to see if they have a significant impact on the results, or if their effect is merely marginal. Nevertheless, for the sake of simplicity and efficiency, we opted for evaluating just the influence of the selection mechanism, as it is the accessory assumption that seemed more likely to be responsible for the variability observed, and its relevance has been previously shown in the literature (Galán and Izquierdo, 2005).

In particular, in our robustness assessment we compared the effect of the original selection mechanism –random tournament– with that of three alternative selection mechanisms, namely roulette wheel, standard deviation and average selection, while maintaining the mutation process unaltered with respect to the original implementation. Remarkably, the four selection mechanisms under scrutiny would be equally plausible within the framework of the CURP model. For a brief description of their specifics please refer to the full article (chapter 4).

Outstandingly, the results obtained with these three alternative selection mechanisms do not differ significantly from those obtained with the original random tournament mechanism. In fact, the three regimes identified in the original work continue to emerge in all the three alternative implementations, being the variations with respect to the original results very subtle. Actually, the only remarkable difference is that in the low-stress regime the new experiments present greater variability. Nonetheless, such increased variability is what could be expected, since in the three new selection mechanisms the probability of changing the strategy is greater than in random tournament, where it is mainly driven by mutation. In particular, leaving aside the mutation process, the fact is that the three new mechanisms mix and reshuffle the population strategies more intensively, hence expediting more movement in the average population strategy at each run. Remarkably, roulette wheel is the one inducing greater variability –as it can be seen in the results (Zurro et al., 2019).

In addition, the average results of *correlation* and *given-energy* are equivalent to the original ones for the three regimes identified, which strongly suggests that these regimes are in fact stability points of the model, as they are robust to the selection mechanism, i.e., they are not affected by the different selection dynamics that can be imposed. Hence, this study has served to improve the reliability of the CURP model and thereupon, to increase our confidence in its results and the conclusions drawn from them.

2.5 NETWORK SCIENCE

Network Science –also known as Network Theory or the science of connectivity– is a multidisciplinary research field devoted to the analysis of connected systems. Remarkably, its multidisciplinary nature stems from the fact that it draws on theories, methods and tools coming from fields as varied as Mathematics, Physics, Computer Science, Statistics and Sociology –among others– (Barabási, 2016c). As a result, it provides an extensive set of tools for the conceptualisation, modelling, analysis and interpretation of interconnected systems.

As its name may suggest, the key element common to all Network Science is networks. A network is a formal abstraction of the components of a system –the nodes or vertices– and the interactions between them –the links or edges– (Newman, 2018). Notably, multiple systems coming from very different fields –see for instance Sociology, Anthropology, Economics, Physics, Environmental Sciences and Health, to cite a few– can be thought of as networks; in particular, Network Science is extensively used for the analysis of complex systems, since, as noted in (Barabási, 2016c), for each complex system it is possible to identify a network that encodes the interactions between the system's components.

At present, as a consequence of the increasing interconnectedness of the world and of the subsequent pervasiveness of networks, the Network Science field is more active and fertile than ever. Thereupon, trying to comprehensively review all its research lines and its major advances would be simply too ambitious. Hence, here we will just try to provide a general overview of the field by covering: (i) the basic network-related concepts, (ii) the most relevant characteristics of networks, (iii) the most common metrics and analyses: centrality measures, local-structure-related measures and community detection.

BASIC NETWORK-RELATED CONCEPTS

The three core concepts of Network Science are *network*, *node* and *link*. The relation between the three becomes evident in the definition of network provided by Barabási (2016b): “a network is a catalog of a system’s components often called *nodes* or *vertices* and the direct interactions between them, called *links* or *edges*”. Fig. 3 provides an illustrative example of what a network looks like.

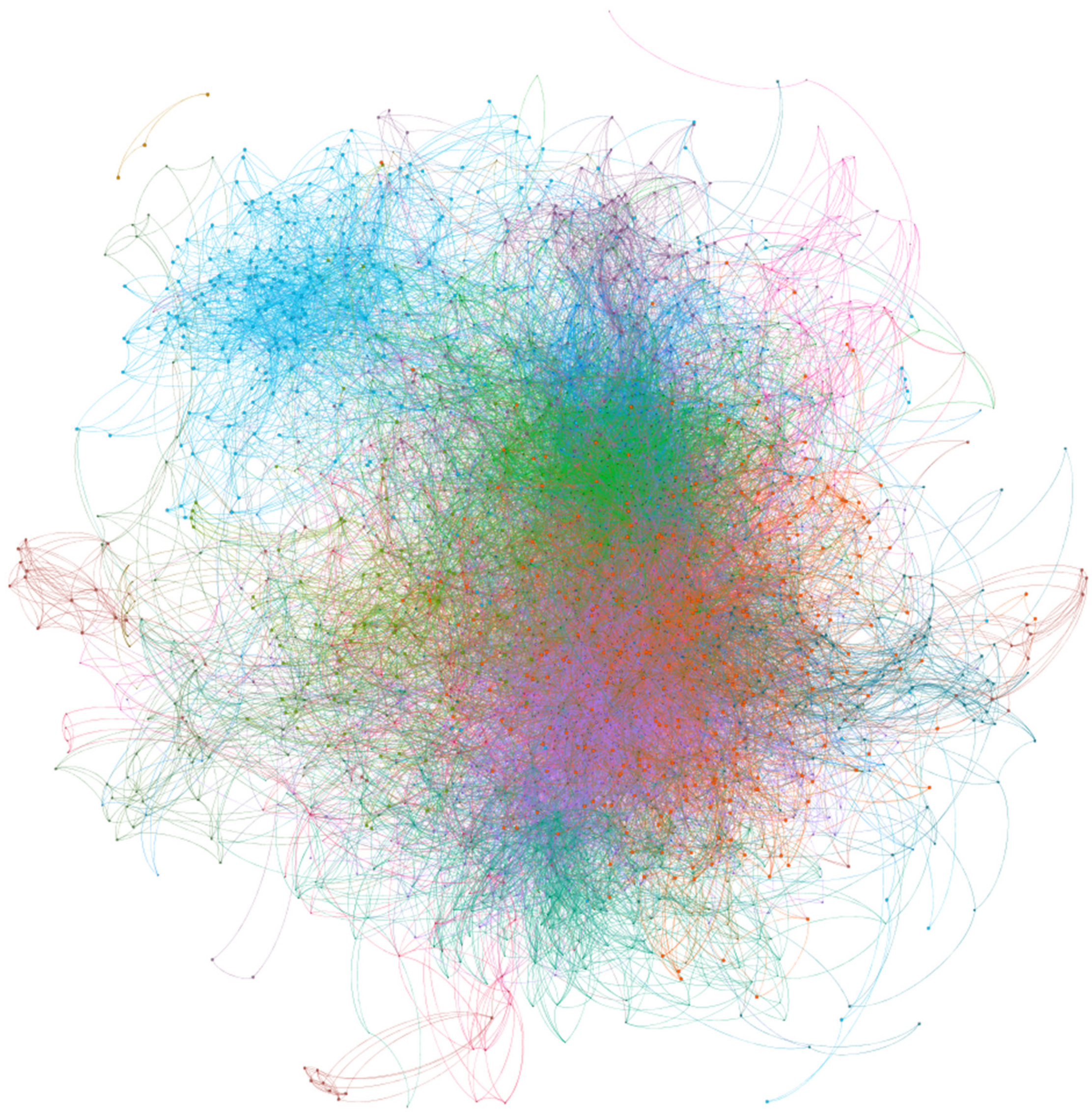

Fig. 3. The picture shows the co-participation network of scholars in thesis committees in the field of Organization and management of enterprises in Spain (Garrido-Labrador et al.). The nodes correspond to the different academics and the weight of the links indicates the number of times they have shared a thesis committee together. The image represents the principal component of the network filtered to academics with a weighted degree of at least 10. The colors denote the different communities detected maximizing the modularity using Louvain's algorithm (Blondel et al., 2008).

First of all, it is important to clarify that the edges of a network may represent anything, but always the same thing in the whole network. Consequently, the choice of what a link represents is of paramount importance, as it determines the questions that we will be able to answer.

Based on the different node variants, networks are classified into: (a) unimodal networks –nodes of a single class–, (b) bimodal networks –nodes of two distinct classes– or (c) multimodal networks –nodes of multiple classes.

As regards the edges of the network, they can be of many types, which in turn translates into a wide range of network typologies. The criteria by which edges –and subsequently networks– can be classified may be summarised as follows:

- Undirected vs. directed edges (networks) → An undirected edge represents a symmetrical relation between two nodes, i.e., a relation that is identical in both senses; undirected edges are typically represented by a simple line. On the other hand, a directed edge has both a source and a target node, being it generally represented by an arrow. Recall that, by extension, an undirected network is a network with undirected edges, while a directed network is a network whose edges are directed.
- Simple vs. multiple edges (networks) → A multiple network is a network that has two or more edges between the same pair of nodes and/or self-edges –i.e., edges whose source and target nodes are the same–. Otherwise, i.e., if between a pair of nodes only one edge exists, the network is simple.
- Unweighted/binary vs. weighted edges (networks) → An unweighted network has unweighted edges –i.e., edges with no weight attribute–, which implies that those edges only represent the existence of a relation of the given type. Alternatively, a weighted network is a network whose edges have a weight attribute –i.e., a positive/negative quantitative value that weights the relation.

Further relevant subdivisions and/or interesting particular cases of the previous network typologies include:

- Cyclic vs. acyclic directed networks → A cycle in a directed network is a closed loop of edges whose arrows point in the same way around the loop. In this regard, it is noteworthy that a self-edge counts as a cycle. Accordingly, a directed network that presents cycles is called cyclic, whilst a directed network that has no cycles is acyclic

(Newman, 2018). The rule of the thumb to determine whether a directed network is acyclic says: “if the network can be spatially represented so that all the arrows of the edges point downward, then the network is acyclic”. The citation network of papers is a paradigmatic example of acyclic directed network.

- <u>Bipartite networks</u> → A bipartite network is a particular case of bimodal network – i.e., a network with two kinds of nodes– such that the edges run only between nodes of unlike type. The most archetypal example of a bipartite network is the network of films and actors, where the actors constitute one type of nodes, being the other type the films in which they star. Noteworthily, bipartite networks can always be projected into two unimodal networks.
- <u>Multimodal networks</u> → Previously, we defined a multimodal network as a network with nodes of multiple classes. As a matter of fact, in a multimodal network both nodes and edges can be of different classes. Concretely, a multimodal network is a heterogeneous network where each node belongs to a particular mode/class while edges belong to a given kind of interaction between two modes. An illustrative example is that of a biological network in which genes, diseases and drugs constitute the node’s modes, and the different interactions modelled include disease-disease, disease-gene, gene-drug and disease-drug.
- <u>Complex networks</u> → A complex network has two defining features: (i) it has a very large number of nodes and (ii) its topological features are non-trivial, i.e., the interconnection patterns between the nodes are neither entirely regular nor purely random. Notably, these two characteristics are common in networks representing real systems.

Eventually, a last aspect that needs to be tackled in this section is that of network representation. Notably, there are different ways to represent a network mathematically, being the most frequent: (i) as an edge list, (ii) as an adjacency list and (iii) as an adjacency matrix. Among the three of them, the adjacency matrix is probably the most common one.

The adjacency matrix A of a binary undirected network $B\ (N, L)$ consisting of a set of nodes $N = \{1, 2, \cdots, n\}$ and a set of edges $L \in NxN$ would be mathematically defined as follows:

$$A_{ij} = \begin{cases} 1 \text{ if there exists an edge between nodes } i \text{ and } j \\ 0 \text{ otherwise} \end{cases} \qquad (1)$$

Adjacency-matrix remarks:

- Should the network be weighted, then the elements of the adjacency matrix represent the weights of each edge.
- In the case of a directed network, the edge formalism (i, j) means that there is an edge with *j* as the source node and *i* as the target node; however, this does not imply the existence of the edge (j, i).

Most relevant characteristics of networks (Barabási, 2016b; Newman, 2018):

- Network size → Number of nodes of the network (N). Networks with less than N = 10 are deemed small networks, while networks with more than N = 1000 are considered big networks.
- Density → The density of a network is the quotient between its actual number of edges (L) and the maximum possible number of edges. Recall that in a simple graph –i.e., one with no multiedges or self-edges– the maximum possible number of edges is:

$$\binom{N}{2} = \frac{1}{2}N(N-1) \tag{2}$$

- Thus, being the density of the network calculated as:

$$\rho = \frac{L}{\frac{1}{2}N(N-1)} \tag{3}$$

In relation to density, a network is said to be sparse when the number of edges is of the same order as the number of nodes ($L \approx N$). On the other hand, a network is considered to be dense if $L \gg N$.

- Degree (k_i) → It is a property of the node; in an undirected network the degree of a node represents the number of edges it has to other nodes. In directed networks, two different degrees are defined:
    - In-degree → The number of ingoing edges connected to a given node.
    - Out-degree → The number of outgoing edges of a node.
- Average degree $\langle k \rangle$ → It is a property of the network. In an undirected network it is calculated as follows:

$$\langle k \rangle = \frac{1}{N}\sum_{i=1}^{N} k_i = \frac{2L}{N} \tag{4}$$

- In a directed network there are two average degrees: the average in-degree $\langle k^{in} \rangle$ and the average out-degree $\langle k^{out} \rangle$:

$$\langle k^{in} \rangle = \frac{1}{N}\sum_{i=1}^{N} k_i^{in} = \langle k^{out} \rangle = \frac{1}{N}\sum_{i=1}^{N} k_i^{out} = \frac{L}{N} \tag{5}$$

- Degree distribution (p_k) → The degree distribution provides the probability that a randomly selected node in the network has degree k. It is important to note that the degree distribution determines many network properties and multiple network phenomena.
- Distance and geodesic distance (d) → In networks, the concept of distance is not related to physical distance but to the number of edges passed through to get from a source node to a target node. As a matter of fact, there may be multiple paths between two nodes, being the *shortest path* the one with the fewest number of edges. The distance between two nodes i and j is commonly expressed in terms of the *geodesic distance*, that is, the length of the shortest path between the two.

It should be recalled that in a weighted network the shortest path is the one with the lowest sum of weights.

- Diameter (d_{max}) → It is the largest distance between any pair of nodes in the network, that is, the maximum shortest path.
- Average path length $\langle d \rangle$ → It is the average distance between all pairs of nodes in the network, i.e., the average of all the shortest paths between all pairs of nodes.
- Component → A component is defined as the largest set of nodes such that there exists at least one path between each pair of nodes. A network is connected if it consists of a single component, that is, if at least one path exists between each pair of its nodes. Note that in the case that no edge exists between a pair of nodes, the distance between the two is $d_{ij} = \infty$. Provided that in a network there exists at least a pair of nodes (i, j) such that $d_{ij} = \infty$, then the network is disconnected, that is, it consists of different connected components that are not connected to each other.
- Giant component → In undirected networks, it is frequent to find that a significant proportion of the nodes (around 90%) belong to the same component; such a component is called giant component, being the rest of the nodes distributed in a large number of small components.

MOST COMMON METRICS AND ANALYSES (NEWMAN, 2018)

This section is subdivided into three different blocks: (1) centrality measures, (2) local-structure-related measures and (3) community analysis.

CENTRALITY MEASURES

This first block is devoted to the exploration of some standard metrics that are used to quantify the network topology. More specifically, our focus is on centrality measures, that is, on metrics conceived to determine the relative importance of a node in the network according to different criteria. Importantly, no centrality measure is better than the others, being their suitability and usefulness dependent on the nature of the problem and of the relations being studied (Newman, 2018).

- Degree centrality → The simplest centrality measure is the degree of the node, that is, the number of edges connected to it. The rationale behind using degree as a centrality measure is to be found in social networks, where it is sensible to think that those individuals with a greater number of connections may have more influence, more access to information or more prestige than individuals who are poorly connected to others.
- Eigenvector centrality → Even though degree centrality may be useful and enlightening in some cases, the truth is that in many circumstances the importance of a node is increased not just by its number of connections, but by having connections to nodes that are themselves important. This is the idea behind eigenvector centrality, which gives each node a score proportional to the sum of scores of its neighbours.

More specifically, the centrality x_i' of node i is defined as the sum of the centralities of its neighbours:

$$x_i' = \sum_j A_{ij} x_j \qquad (6)$$

Where A_{ij} is an element of the adjacency matrix. Making the appropriate transformations on the basis of the eigenvector equation ($Ax = \kappa_1 x$) we get:

$$x_i = \kappa_1^{-1} \sum_j A_{ij} x_j \qquad (7)$$

Where A is the adjacency matrix and κ_1 is the largest eigenvalue of A. Therefore, according to the eigenvector centrality, a node can be important because it has many neighbours, because it has important neighbours, or both.

In theory, eigenvector centrality can be calculated for both undirected and directed networks. However, in the case of directed networks complications arise, namely (i) that in a directed network the adjacency matrix is asymmetric, thus existing two sets of eigenvectors (right and left); in such a scenario, assuming that the importance of a node comes from other nodes pointing towards it rather than from it pointing to others, the right eigenvector is usually taken; and (ii) that there can be nodes whose eigenvector centrality is zero in spite of being pointed to by other nodes. A variation of eigenvector centrality that addresses these inconveniences is the Katz centrality.

- Katz centrality → Katz's solution to the aforementioned issues consists in including two positive parameters $\alpha > 0$ and $\beta > 0$:

$$x_i' = \alpha \sum_j A_{ij} x_j + \beta \qquad (8)$$

Where β ensures that all nodes have a non-zero centrality value –for convenience it is usually set to $\beta = 1$– and α modulates the balance between the eigenvector term and the constant term.

- Page Rank → Aside from the issues of eigenvector centrality and how they are approached by Katz centrality, both metrics still present a relevant shortcoming: a node with high centrality (be it eigenvector or Katz) gives also a high centrality to all the nodes it points to. Obviously, this is not always appropriate; in fact, it seems intuitive that the importance gained by receiving an edge from an important node should be downgraded if such prestigious node points to many others. Larry Page's proposal –Page Rank– incorporates such intuition in the following form: "the centrality that a node derives from its neighbours is proportional to their centrality divided by their out-degree"; thereupon, a node with high centrality that points to many others will only pass to them a small portion of its importance, that is, the importance received from a prestigious node is diluted when shared with many other nodes.

Formally, Page Rank centrality is defined by:

$$x_i = \alpha \sum_j A_{ij} \frac{x_j}{k_j^{out}} + \beta \qquad (9)$$

Where α and β continue to be non-zero terms as in Katz centrality and k_j^{out} is the out-degree of node j. Remarkably, equation (9) gives problems if there are nodes with $k_j^{out} = 0$; this issue is, however, easily solved by setting $k_j^{out} = 1$ for all such nodes.

- Hubs and authorities (HITS algorithm) (Kleinberg, 1999) → In the previous three metrics, a node has high centrality if the nodes that point to it have high centrality. Nevertheless, it may also be of interest to bestow a node high centrality if it points to others with high centrality. In this vein, we can define two types of important nodes: *authorities* and *hubs*; an authority is a node whose importance lies in that it contains useful information, while a hub is a node that is important because it informs about where to find the best authorities. Accordingly, we can define two different types of centrality for directed networks, the *authority centrality* and the *hub centrality*, which quantify nodes' prominence in the two roles. This idea was developed into an algorithm known as *hyperlink-induced topic search* –HITS.

  The HITS algorithm gives each node both an authority centrality x_i and a hub centrality y_i. Recall that for a node to have high authority centrality it has to be pointed to by many hubs –i.e., nodes with high hub centrality–, while for a node to have high hub centrality it has to point to many authorities –i.e., nodes with high authority centrality. Remarkably, since these definitions are circular, a node could have both high hub centrality and high authority centrality.

  In strictly mathematical terms, the authority centrality of a node is defined to be proportional to the sum of the hub authorities of the nodes that point to it:

  $$x_i = \alpha \sum_j A_{ij} y_j \qquad (10)$$

  Where α is a proportionality constant. On its part, the hub centrality of a node is proportional to the authority centralities of the nodes it points to:

  $$y_i = \beta \sum_j A_{ji} x_j \qquad (11)$$

  Where β is another constant.

  Noteworthily, the HITS algorithm does not suffer from the issues that the eigenvector approaches present when dealing with directed networks, thus being more suitable for their analysis.

- Closeness centrality → The importance of a node can also be measured in relation to its proximity to other nodes. In particular, the assumption behind closeness centrality is that nodes that are closer to all other nodes in the network have better access to information and/or may be able to convey their opinion faster. Formally, the closeness centrality of a node is defined as the inverse of the mean geodesic distance of a node to all other nodes in the network –remember that the geodesic distance between two nodes *i* and *j* is the length of the shortest path between them:

$$C_i = \frac{N}{\sum_j d_{ij}} \qquad (12)$$

Where C_i is the closeness centrality of node i, N is the number of nodes of the network and d_{ij} is the geodesic distance between nodes i and j.

The closeness centrality metric is often used in the study of social networks. Notwithstanding, it important to note that it is not always easy to distinguish between central and less central nodes using it, as geodesic distances between nodes in most networks tend to be small, thus being the differences between the closeness centralities also small.

- <u>Betweenness centrality</u> → This centrality measure considers that the importance of a node is proportional to the number of shortest paths between pairs of nodes that it lies on. In fact, it is the number of geodesic paths that a node lies on what we call betweenness centrality. Notably, the betweenness of a node can be thought of as its degree of intermediation between all nodes in the network.

  Mathematically, the betweenness centrality of node i is given by:

$$x_i = \sum_{st(s \neq t)} n_{st}^i \qquad (13)$$

Where $n_{st}^i = \begin{cases} 1 \text{ if vertex } i \text{ lies on the shortest path from } s \text{ to } t \\ 0 \end{cases}$

Recall that the above equations only hold for the case in which there is at most one shortest path between each pair of nodes. However, there may be more than one. Therefore, to account for such possibility betweenness centrality is typically extended in the following form: for each pair of nodes, it gives each shortest path a weight equal to the inverse of the number of geodesic paths between the two. Formally:

$$x_i = \sum_{st(s \neq t)} \frac{n_{st}^i}{g_{st}} \qquad (14)$$

Where n_{st}^i is now redefined as the number of geodesic paths from s to t that pass through i, g_{st} is the total number of geodesic paths from s to t, and $\frac{n_{st}^i}{g_{st}} = 0$ by convention when both n_{st}^i and g_{st} are equal to zero.

LOCAL-STRUCTURE-RELATED MEASURES

- <u>Transitivity</u> → In Mathematics, a relation "O" is transitive if:

$$\begin{cases} AOB \\ BOC \end{cases} \rightarrow AOC \qquad (15)$$

A typical example of transitive relation is that of equality: if $a = b$ and $b = c$, then it follows that $a = c$.

In networks, for a set of nodes $\{n_1, n_2, n_3\}$ the relation "connected by an edge" is said to be transitive if existing the edges (n_1, n_2) and (n_2, n_3), then (n_1, n_3) exists as well. Therefore, a friendship network is said to be transitive if "the friend of my friend is also my friend".

It should be noted that perfect transitivity only occurs in networks that are fully connected; consequently, it is not very informative per se. Notwithstanding, partial transitivity can indeed be very useful. Actually, in manifold networks, and particularly in social networks, even though the fact that n_1 knows n_2 and n_2 knows n_3 does not guarantee that n_1 knows n_3, the truth is that it is far more likely that n_1 knows n_3 than any other node from the network chosen at random. Continuing with the friendship example, if n_1 knows n_2 and n_2 knows n_3, then we have a path $n_1 - n_2 - n_3$ of length two; should n_1 also know n_3, then the path is closed, i.e., n_1, n_2 and n_3 form a closed triad.

- Clustering coefficient of the network → Formally, the level of transitivity of a network can be quantified by means of the *clustering coefficient of the network*, which is defined to be the fraction of closed paths of length two in the network:

$$C = \frac{(\text{number of closed paths of length two})}{(\text{number of paths of length two})} \tag{16}$$

Note that C takes values within the range from 0 to 1, with $C = 0$ meaning that no closed triads exist, and $C = 1$ implying perfect transitivity. Interestingly, social networks tend to have high values of the clustering coefficient in comparison to the expected value if the links were established at random.

- Clustering coefficient of a node – Local clustering coefficient → The clustering coefficient can be defined both for the network as a whole –equation (16)– and for a single node –equation (17). For node i, its clustering coefficient C_i is defined as:

$$C_i = \frac{(\text{number of pairs of neighbours of } i \text{ that are connected})}{(\text{number of pairs of neighbours of } i)} \tag{17}$$

Recall that the local clustering coefficient represents the average probability that a pair of i's friends are friends of one another.

Local clustering is interesting for several reasons, outstanding among which are: (i) its empirically found inverse relation to degree: nodes with higher degree have on average a lower local clustering coefficient; and (ii) its usefulness for the detection of structural holes, i.e., missing links between the neighbours of a node, that is, neighbours that are not connected to one another. In relation to this second utility, the fact is that the local clustering coefficient can be regarded as a type of centrality measure, one in which the most powerful individuals are those with the lowest values of the local clustering coefficient, as the lowest the local clustering of a node, the greater its control over the flow of information between its neighbours. In this vein, the local clustering coefficient can be seen as akin to betweenness centrality, with the only caveat that while betweenness centrality measures the node's intermediation over all pairs of nodes in the network –or in the node's component–, local clustering just assesses the control over information flows across the immediate neighbours of the node. Therefore, the local clustering coefficient is typically seen as a local version of betweenness centrality. Interestingly, in practice betweenness and local clustering are strongly correlated; hence, since the calculation of betweenness centrality is significantly more computationally intensive than that of local clustering, in certain contexts it could be of interest to use local clustering as proxy for betweenness centrality.

- Reciprocity → In directed networks, it is also of interest to quantify the frequency of loops of length two, i.e. the number of pairs of nodes between which there are directed edges running in both directions; that is precisely what reciprocity measures, the probability that a node that you point to also points back at you. Accordingly, if in a directed network there is a directed edge from node *i* to node *j* and there is also an edge from node *j* to node *i*, then we say that the edge (i, j) is *reciprocated*.

  Formally, reciprocity (r) is defined as the fraction of edges that are reciprocated, that is:

  $$r = \frac{1}{m} \sum_{ij} A_{ij} A_{ji} \tag{18}$$

  Where *m* is the total number of directed edges in the network, and the product of adjacency matrix elements $A_{ij}A_{ji}$ is:

  $$A_{ij}A_{ji} = \begin{cases} 1 \text{ if and only if there is and edge from } i \text{ to } j \text{ and an edge from } j \text{ to } i. \\ 0 \text{ otherwise} \end{cases}$$

- Similarity → Similarity measures are aimed at determining the similarity between the nodes of a network by use of the information contained in the network structure. There exist two main types of similarity measures: *structural equivalence* and *regular equivalence*; two nodes are structurally equivalent if they share many of their neighbours, while they present regular equivalence if they have neighbours that are themselves similar –i.e., regular equivalence does not necessarily imply to have the same neighbours, but that their neighbours are similar. The most common measures of structural equivalence cosine similarity and Pearson coefficient. Remarkably, quantitative measures of regular equivalence are less developed than measures of structural equivalence.

- Homophily or assortative mixing → Homophily is the tendency of individuals to associate with similar others, i.e., with individuals whom they perceive as being similar to themselves with respect to some criteria such as age, sex, ethnicity, etc. Within the framework of networks, suppose that we have a network in which nodes are classified in accordance with an enumerative attribute that has a finite set of possible values; such network is said to be assortative if a significant fraction of the edges runs between nodes of the same type.

To measure the homophily of a network with respect to a given characteristic, the metric typically used is modularity, which is defined as:

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right)\delta\left(c_i, c_j\right) \qquad (19)$$

Where A_{ij} is the actual number of edges between nodes i and j and $\frac{k_i k_j}{2m}$ is the expected number of edges between the two if edges were placed at random. Eventually, $\delta\left(c_i, c_j\right)$ -the Kronecker delta- indicates if the two nodes belong to the same class or not:

$$\delta\left(c_i, c_j\right) = \begin{cases} 1 \text{ if both } i \text{ and } j \text{ belong to the same class} \\ 0 \text{ otherwise} \end{cases} \qquad (20)$$

Recall that the expression of modularity in equation (23) has been normalised –it is divided by the number of edges *m*–, and thus it is strictly less than 1, taking positive values if there are more edges between nodes of the same type than would be expected by chance, and negative values if there are less.

MOST COMMON COMMUNITY DETECTION ALGORITHMS

In Network Science communities are typically defined as groups of nodes that are more densely connected internally than with the rest of the network. In other words, a community is as a set of nodes with dense intra-community connections and sparse connections to other communities (Barabási, 2016a). From these definitions, it becomes evident that communities are local structures, as they constitute regularities that are observed at intermediate scales – i.e., scales that lie between the individual node-level and the entire network.

Notably, most real-world networks exhibit a markedly modular structure –that is, they have community structure–, being thus of interest to identify and analyse those communities. More precisely, the relevance of community detection and of the subsequent community analyses is explained by several reasons that include –among others–: (i) the fact that communities often have properties that are very different from the global average properties of the network, being it more appropriate to calculate module-specific metrics; (ii) their impact on different network dynamics such as information flow, epidemic spreading, etc.; and (iii) the potential of their study to generate new knowledge, be it purely descriptive or goal-oriented –e.g. understanding the formation dynamics of certain groups, determining the best way of isolating communities, etc.

Consequently, the field of community detection has experienced a tremendous growth in the last decades, existing at present a vast number of community detection algorithms that provide very different approaches and alternatives for the various circumstances that one may encounter. In the present methodological framework, for the sake of simplicity, we will just focus on two of the most famous ones, namely the Louvain method for community detection and the Newman-Girvan algorithm. However, the interested reader can refer to (Fortunato, 2009) for a comprehensive review of the different methods and algorithms.

It is important to note that both Louvain and Newman-Girvan are based on the maximisation of modularity, which, in the context of community detection, quantifies the quality of an assignment of nodes to communities; recall that it does so by comparing the actual number of intra-community edges with the expected number of intra-community edges if they were established at random. Theoretically, the optimisation of modularity yields the best possible grouping of nodes of a given network. Notwithstanding, since exploring all the possible community assignments is both impractical and extremely time-consuming, heuristic algorithms used instead. Here below we provide the details of the heuristics implemented in the Louvain and Girvan-Newman algorithms.

- Louvain method for community detection (Blondel et al., 2008) → This method implements a hierarchical clustering approach and consists of two phases. Phase 1 starts by assigning each node to its own community; then, for each node *i*, the change in modularity that would result from moving it from its original community into the community of each of its neighbours is calculated. Eventually, node *i* is assigned to the community that induced the greatest modularity increase. This process is applied repeatedly and sequentially to all nodes until no increase in modularity occurs. Once this happens, it is time to move to Phase 2. In Phase 2, a new network is built where the nodes are the communities from Phase 1 –i.e., each community from Phase 1 is condensed into a single node–, the edges between nodes of the same community are now represented as self-edges, and the edges from different nodes in the same community to a given node in a different community are now represented by a weighted edge between communities. Once the new network is built, the process of Phase 1 is applied to it.

- Newman-Girvan (Newman and Girvan, 2004) → This approach is based on the iterative removal of edges from the network to split it into communities. More specifically, the sequence of the algorithm may be summarised as follows:
  1. Calculate the edge shortest-path betweenness of all edges in the network.
  2. Remove the edge with the highest shortest-path betweenness.
  3. Recalculate the shortest-path betweenness of all edges after the removal. (Note that alternatively, one can just recalculate the shortest-path betweenness of the edges affected by the removal, which may lessen the running time of the algorithm).
  4. Steps 2 and 3 are repeated until no edges remain.

  It should be noted that every time the network is broken into a new set of components, the modularity of such community assignment is calculated and recorded. Eventually, the partition with the highest modularity value is proposed as the best solution.

USE OF NETWORKS IN THE PRESENT THESIS

In the present thesis, Network Science was used within the framework of the scientific publication entitled: “Quantifying the relationship between food sharing practices and socio-ecological variables in small-scale societies: A cross-cultural multi-methodological approach”.

In this contribution, a sharing similarity network was built to verify whether geographically closer societies exhibit more similar sharing practices, that is, to explore such hypothesis in the light of empirical evidence. To that end, the 22 small-scale societies subject to study were set as nodes, being an edge established between two societies if they had in common a basic sharing practice. The network was subsequently transformed into a weighted network in which the weight of each edge represents the number of basic sharing practices that the two societies have in common. Eventually, the network was represented in a real-world map, being the different societies (nodes) placed in accordance with their geographic location. After a qualitative assessment of such network visualisation, the main conclusion obtained was that geographic distance does not seem to correlate with dissimilarity in sharing practices, as societies whose practices are more similar –i.e., those linked by the edges with higher weight– are found to be significantly distant in space. For further details, please refer to the full article –chapter 5.

2.6 DATA SCIENCE, ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING.

We live in the age of data. As a consequence of technological development in general and of that of the ICT in particular, almost everything in our lives leaves a digital footprint. As a result, we have at our disposal a data deluge that, if successfully exploited, holds the potential to enhance our understanding of the world and our capacity to act on it. Therefore, there exists a clear need to process, store, analyse and comprehend vast amounts of data in meaningful ways. This is where the different data analysis techniques come into play.

In relation to data analysis techniques, the first thing to note is that much hype and confusion surround their terminology. In fact, terms such as Data Science, Artificial Intelligence and Machine Learning are often used interchangeably and typically conflated with each other. In this regard, it is important to note that their definitions are not uncontested in the literature and that the boundaries between them are markedly fuzzy. For this reason, in this section we first clarify what we understand under each of those terms, to later focus on Machine Learning and its different tools, which are precisely the data analysis techniques that we have used the most in the present thesis.

CLARIFICATION OF TERMS

The fields of Artificial Intelligence, Machine Learning and Data Science are closely related to each other, existing significant overlaps between them. As previously noted, there exists no consensus as to how to define them or where to place the boundaries between the three. Consequently, here below we proceed to outline their main characteristics and the relationships between them in a very general fashion, so that the different concepts and techniques may be better understood and adequately placed within the more general framework to which they belong.

ARTIFICIAL INTELLIGENCE (AI)

AI is about giving machines the capability of mimicking human behaviour in general and cognitive functions in particular (Kotu and Deshpande, 2019). More specifically, AI seeks to build intelligent entities that use perceptions from the environment to perform actions that maximise some measure of performance. Notably, in some cases machines have exceeded by far human capabilities, whilst in others they are barely just beginning to scratch the surface.

The most remarkable techniques falling under AI include –but are not limited to–: linguistics, text mining, computer vision, robotics and Machine Learning. Recall that since learning is an important human capacity, Machine Learning is typically considered as one of the most prominent tools of AI. However, it can alternatively be regarded as a field in its own right.

MACHINE LEARNING (ML)

ML is the study of computer algorithms capable of learning to improve their performance of a task through experience (Mitchell, 1997). Notably, experience for machines comes in the form of data. More precisely, so that machines can learn, it is necessary to teach them; the data used to teach them is called *training data*.

At this point, it is important to make clear the difference between a computer program in the traditional sense and a ML algorithm. While every computer program consists of a set of instructions or predefined rules in accordance to which inputs are transformed into outputs, ML algorithms –also known as “learners”– take both input and output from a known dataset –the training data– to come up with a model of the program that converts input into output. Put another way, learners generalise a pattern that is identified on a particular set of data (Kotu and Deshpande, 2019).

ML is typically divided into three large groups according to the kinds of problems being addressed: *supervised learning* –when the data used for learning are labelled–, *unsupervised learning* –if the data are unlabelled– and *reinforcement learning* –when the agent’s behaviour is aimed at maximising a given fitness function–. The specifics of these subdivisions are covered in detail in the section entitled “ML Subcategories”. Recall however, that since in the present thesis we have only applied supervised and unsupervised learning techniques, reinforcement learning will be addressed just tangentially.

DATA SCIENCE

Data Science is the umbrella term used to designate the application of AI, ML and additional techniques coming from other quantitative fields such as Statistics and Mathematics to extract value from data, that is, useful patterns and meaningful structures. The key features and motivations of Data Science may be summarised as follows (Kotu and Deshpande, 2019):

- **Identifying meaningful structures** within a dataset; recall that by meaningful structures we refer to nontrivial, valid, novel, potentially useful and ultimately understandable patterns that may serve to inform decisions, to better understand the matters at hand and/or to induce generalisations.
- **Building representative models** that fit the observational data and that, after the due generalisation of the input-output relationships found, can be used for either predictive or explanatory purposes.
- **Interdisciplinary nature.** In view of the ever-growing data flood, Data Science borrows computational techniques from the fields of Statistics, Computer Science, ML and database theories so as to be able to store, process and analyse large datasets in the pursuit of unravelling useful and relevant patterns.
- **Iterative approach.** Like many quantitative frameworks, Data Science is iterative, i.e., further information about the patterns present in the data is gained in each cycle.
- **Key role of subject matter expertise.** One of the key ingredients of successful Data Science is substantial prior knowledge about the data themselves and the processes that generate them, what is known as *substantive knowledge* or *subject matter expertise*.

As regards the classification of data science problems, there are two main approaches: (i) they can be categorised into supervised and unsupervised in accordance with the criteria described in the context of ML; and (ii) they can also be classified around the different tasks they encompass; the proposal by Kotu and Deshpande (2019) in that regard consists of the following tasks:

- **Regression –** Predict a quantitative target label of a datapoint based on learning from a training set.
- **Classification** – Predict a qualitative target label –the class– of a datapoint based on learning from a training set.
- **Deep learning –** Use of sophisticated artificial neural networks for classification and regression problems.
- **Clustering** – Identify the natural groupings in a dataset based on the relationship between the data points themselves.
- **Feature selection** – Reduce the attributes in a dataset into the those that are actually important for the intended purpose.
- **Association analysis –** Identify relationships within an item set. Its most archetypal application is what is called the *market basket analysis*, i.e., the identification of pairs of items that are typically purchased together
- **Text mining –** Application of text processing techniques to textual documents so that after those documents have been transformed into vectors/arrays, other tasks such as classification and clustering can be applied to them.

- **Anomaly detection** – Predict if a data point is an outlier by comparison to other datapoints in the dataset.
- **Time series forecasting –** Predict the future value of a variable based on past historical values
- **Recommendation engines** – Recommend items to users based on individual user preference.

In any case, it should be noted that this is just a particular reading of how the different branches of Data Science can be structured, and as such it should be considered only if it is useful, as different alternative conceptualisations would be equally valid.

ML SUBCATEGORIES

Having outlined the general framework to which AI, ML and Data Science belong, as well as some of the most relevant details regarding their scope and respective subcategories, in this section we proceed to explore more in detail the three main groups into which ML is typically subdivided –namely *supervised learning*, *unsupervised learning* and *reinforcement learning*–, with a special focus on supervised and unsupervised learning in general, and on the specific techniques applied in this thesis in particular.

SUPERVISED LEARNING

Supervised learning techniques are intended for the type of problems in which each observation –codified as a vector with the corresponding values for the different predictor variables– has an associated response variable, i.e., a label. In particular, supervised learning methods seek to learn a function that maps the set of input variables –the predictors– into an output –the response variable– based on a sufficiently large training sample of input-output pairs (James et al., 2013). Thereupon, the output of a supervised learning algorithm is a model that relates the response to the predictors and that is typically used either for predictive or explanatory purposes. Recall that if the final aim is prediction, we intend to accurately predict the response for new –unseen– observations, whilst if the aim is explanation, it is the relationships between the response and the predictors that we are interested in understanding.

Supervised learning problems are, in turn, divided into two main categories based on their response variable: regression problems –quantitative response– and classification problems –qualitative response–. Notably, a broad range of supervised learning algorithms have been developed for each problem typology, existing also methods that can be used for both quantitative and qualitative responses.

The most widely used supervised learning algorithms include (James et al., 2007; Hastie et al., 2009): (i) linear methods both for regression and classification –with and without regularisation–; (ii) nearest neighbour methods; (iii) linear discriminant analysis (LDA); (iv) tree-based methods –decision trees, bagging, boosting, random forest, rotation forest–; (v) Support Vector Machines (SVM); and (vi) artificial neural networks –Multilayer perceptron–.

It is important to highlight that no supervised algorithm is better than the others in all cases (Wolpert, 1996), being thus the choice of the algorithm strongly dependent on the context. Nevertheless, according to recent research (Fernández-Delgado et al., 2014), there are certain algorithms that have proved more likely to perform better, namely random forest, SVM, neural networks and boosting ensambles. Consequently, when faced with a new problem, it is always a good idea to begin with them. That is precisely what we have made in the three articles of the present thesis in which we have applied supervised learning techniques –articles 1, 3 and 4–.

BIAS-VARIANCE TRADE-OFF AND THE INTERPRETABILITY OF THE MODEL

Eventually, two last issues need to be addressed that are related to model selection: the bias-variance trade-off and the model's interpretability, which, in turn, are deeply intertwined. The bias-variance trade-off makes reference to the fact that to build a good supervised learning model, that is, one with high predictive accuracy, we need to minimise the total error, which consists of three elements: the bias –i.e., the difference between the average prediction of our model and the real target value we are trying to predict–, the variance –i.e., how much the predictions for a given point vary between different realisations of the model– and the irreducible error:

$$\text{Total error} = \text{BIAS}^2 + \text{Variance} + \text{Irreducible error} \tag{21}$$

Consequently, one would ideally seek to find an algorithm with both low bias and low variance. However, it is not that straightforward, since bias and variance constitute opposing phenomena, that is, one grows when the other decreases; this is precisely why we speak of a trade-off. Typically, more complex models with a flexible underlying structure present high variance and low bias –they overfit the training data– while simpler models with less parameters and a more rigid structure present low variance and high bias –they suffer from underfitting. Notably, those models with greater complexity and higher variance will also be more difficult to interpret, while simpler models will be more straightforwardly understandable. For all the above, the point to be made is that model selection cannot be made exclusively on grounds of predictive accuracy; both the context of application and the model's intended purpose have to be considered as well. In fact, the model's purpose is the most determining factor since, depending on whether we are interested in explanation or prediction, we will give priority to interpretability over predictive accuracy or viceversa.

VARIABLE IMPORTANCE ANALYSES

An additional remark in relation to interpretability is linked to variable importance analyses. More specifically, if the supervised model being fit is an ensemble, even though a priori it is much more difficult to interpret than other approaches such as single-tree models, the fact is that we have the possibility to conduct both individual and/or group variable importance analyses to shed light into its internal dynamics. Notably, within the framework of the present thesis we have conducted variable both individual and group variable importance analyses in two out of the four articles, namely article 1 and article 4. In both cases, the base ensemble model was a random forest used for classification purposes.

The details of variable importance analysis within the framework of a random forest classifier may be summarised as follows: once the model is fitted, for each bootstrapped sample we have a tree fitted to it and the corresponding out-of-bag (OOB) sample –when bootstrapping, data are randomly sampled with replacement, which translates into approximately one third of the observations in the real dataset being left out from the bootstrapped sample (James et al., 2013). Let us assume that such real dataset has M predictors; to determine the relative importance of the mth predictor, its values are randomly permuted in all the OOB samples and then, those noised OOB samples are run down their corresponding trees. As a result, each OOB observation obtains several class label predictions –the quantity of which depends on the number of OOB samples where it appears. Eventually, from all the class votes obtained, the majority vote is taken, and it is compared with the true class label to compute the misclassification rate. The importance of the mth predictor will subsequently be calculated as the change in classification accuracy after the permutation with respect to the original case (mean decrease in accuracy).

If instead of individual variables it is groups of variables and their joint importance that we are interested in, then group variable importance analysis will be our tool of choice; more specifically, we will be using the approach in Gregorutti et al. (2015), which –again within the framework of random forest– adapts the individual permutation importance described above to groups of variables. In particular, their method consists in using the same random permutation for each variable of the group under consideration, so that the empirical joint distribution of the group of variables is preserved; note, however, that the link between such group of variables, the rest of predictors and the response is effectively broken.

To conclude, for the details on the different supervised learning algorithms used in this thesis and the justification of their respective choices, please refer to the specific articles –chapters 3, 5 and 6–. Recall that in all the three articles, supervised learning models have been used with a predominantly explanatory purpose, that is, to identify and understand the relationship(s) between the output variable and the input variables. Only in the context of article 1 –chapter 3– the supervised learning model obtained has a clear predictive intention as well, since, in that case, being able to predict the nautical or pedestrian mobility type of a new site/occupation on the basis of its technological features does actually have scientific value.

UNSUPERVISED LEARNING

Unsupervised learning is the subfield of ML devoted to uncovering hidden patterns in unlabelled data with a minimum of human supervision. It is referred to as unsupervised since no response variable guides the analyses (Hastie et al., 2009; James et al., 2013), that is, since there are no output variables to predict. More specifically, unsupervised learning techniques seek to identify and/or understand the relationships either between variables or between observations, hence being generally applied within the framework of exploratory data analysis. Under the umbrella of unsupervised learning we find a great variety of methodologies, being cluster analysis and Principal Component Analysis (PCA) the most common ones (James et al., 2013).

Cluster analysis consists in identifying groups in a data set, so that the observations within each group share some common features, while observations in different groups are quite different from each other; therefore, it is exclusively based on the relationship between the data points themselves. Notably, clustering is not one specific algorithm itself, but the general task to be solved, existing plenty of different algorithms to that end: *k*-means, hierarchical clustering, density-based clustering, etc.

As far as PCA is concerned, it consists in the calculation of the principal components of the dataset –i.e., the dimensions in feature space along which the data present the greatest variation– and their subsequent use in understanding the data and/or for dimensionality reduction purposes.

As in the supervised learning section, the reader is encouraged to explore more in detail the specifics of each of these methodologies as well as the particular use of them that we have made in the present thesis by referring to chapter 6, which contains the article in which unsupervised learning techniques have been implemented.

REINFORCEMENT LEARNING (RL)

Reinforcement learning is the subfield of ML devoted to solving the RL problem (Sutton and Barto, 1998), in which there is an intelligent agent with a particular goal and an environment with which she interacts. More specifically, the RL problem consists in discerning the actions that such intelligent agent ought to take so as to maximise her cumulative reward. In other words, the aim of RL in ML is to design efficient algorithms that maximise the flow of numerical rewards that an agent receives by interacting with her environment, where her decisions not only affect the immediate reward, but also the upcoming situations, and, through that, all subsequent rewards too (Izquierdo and Izquierdo, 2019). Notably, to that end an adequate balance between exploration and exploitation will have to be attained since, on the one hand, to secure high rewards the agent must repeat past actions that have proved to lead to high rewards (exploitation of current knowledge) but, on the other hand, the agent must also try out new actions since these may lead to even higher rewards (exploration of previously uncharted regions).

SCIENTIFIC PUBLICATIONS

3. HUNTER-GATHERER MOBILITY AND TECHNOLOGICAL LANDSCAPES IN SOUTHERNMOST SOUTH AMERICA – A STATISTICAL LEARNING APPROACH

Ivan Briz i Godino, Virginia Ahedo, Myrian Álvarez, Nélida Pal, Lucas Turnes, José Ignacio Santos, Débora Zurro, Jorge Caro and José Manuel Galán.

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Keywords: Hunter-gatherer, statistical learning, shared technology, random forest, mobility.

1.-ABSTRACT

The present work aims to quantitatively explore and understand the relationship between mobility types (nautical vs. pedestrian), specific technological traits and shared technological knowledge in pedestrian hunter-gatherer (HG) and nautical hunter-fisher-gatherer (HFG) societies from the southernmost portion of South America. To that end, advanced statistical learning techniques are used: state-of-the-art classification algorithms and variable importance analyses. Results show a strong relationship between technological knowledge, traits and mobility types. Occupations can be accurately classified into nautical and pedestrian due to the existence of a non-trivial pattern between mobility and a relatively small fraction of variables from some specific technological categories. Cases where the best-fitted classification algorithm fails to generalize are found significantly interesting. These instances can unveil lack of information, not enough entries in the training set, singular features or ambiguity, being the latter case a possible indicator of interaction between nautical and pedestrian societies.

2.-INTRODUCTION

The identification of human groups, social boundaries and interactions based on material culture lies at the heart of archaeological research. Different methodological approaches have been applied to a broad range of case studies, focusing on diverse dimensions of social materiality (Gosselain, 2000, 2016; Fitzhugh and Kennett, 2010). However, the selection of reliable archaeological markers to tackle with these issues remains a matter of debate.

Coastal settlements offer stimulating case studies to identify distinct groups and to explore connectedness. Exploitation of marine resources provided the scenario for changes in socio-economic organization, as well as for the emergence of new technologies and novel forms of interaction (Mandryk et al., 2001; Bailey, 2004; Erlandson and Fitzpatrick, 2006; Bailey and King, 2011; Erlandson and Braje, 2015).

Among these technological innovations, seafaring was undoubtedly an evolutionary key element for hunter-fisher-gatherer (HFG) populations. Sailing technology not only increased their mobility range allowing the colonization of new territories and biotopes, broadening socio-economic practices (Ames, 2002; Erlandson et al., 2011), but also enhanced social connectedness, reinforcing social identities (Gamble, 1988) and creating new social landscapes.

Hence, several authors emphasized the relevance of distinguishing between nautical and pedestrian populations who inhabited the coasts (Ames, 2002; Marean, 2014; Fleisher et al., 2015). However, from the point of view of HFG archaeology, this distinction remains problematic. Coastal HFG sites are generally classified as nautical or pedestrian based on the exploitation of offshore resources or the appearance of human presence in oceanic islands (Bailey, 2004; Rick et al., 2005). Nonetheless, it is important to be careful when classifying HFG sites as nautical based on the sole presence of intertidal resources, as it has been demonstrated that it is not a direct proof of the existence of seafaring (Ames, 2002).

Despite the interest in distinguishing between coastal societies with and without seafaring technology, no formal assessment considering material culture patterns has been conducted yet. Even though connections between resource procurement and specificity of technologies point to a significant relationship, so far, no formal quantitative evidence confirms the strength of this relationship, neither at individual nor at group level (mesoscale analysis). The general global pattern has not been assessed either. Therefore, the development of analytical procedures to disentangle coastal-inland dynamics in HG and HFG societies has a significant methodological value in the archaeological field (Bang-Andersen, 2012).

In this work, we selected a novel approach based on advanced statistical learning techniques and applied it to HG and HFG societies who inhabited the uttermost part of South America during the Holocene, with the aim of identifying the technological variables that better discriminate between nautical and pedestrian populations. Therefore, in the present case study the term ‘mobility’ refers to the distinction between nautical and pedestrian mobility types.

The archaeological research conducted in this area pointed to the presence of nautical and pedestrian societies, according to the aforementioned proxies for seafaring technology. Moreover, ethnographic observations recorded by European explorers during the XIX and the early XX century confirm the existence of maritime and terrestrial HG and HFG societies in the Fuegian Archipelago (Fitz-Roy, 1839; Lothrop, 1928), including evidence of social interaction and information flow between those populations. Nevertheless, it is worth noting that prior analyses have focused on the geographical distribution of particular items of material culture to trace contacts. Examples of such items are raw materials (Álvarez, 2004; Morello et al., 2012; Pallo and Borrazzo, 2016), decoration patterns of portable art (Fiore, 2006) or singular lithic and bone designs (Scheinsohn, 2010). In contrast, in the present research, we rely on a comprehensive database which encompasses a wide range of technological variables to overcome the fragmentary nature of the archaeological record, thus broadening the analytical capabilities offered by material culture.

The main aim of this work is to explore the relationships between specific technological traits and different mobility and transportation modalities in HG and HFG societies, as well as to unveil the degree of connectedness between nautical and pedestrian communities. The spatial analysis of technological variables in nautical and pedestrian sites allows us to identify technological landscapes (Salomon, 1979), a term that refers to the geographical distribution of technical traits or practices, including uses, designs, and knowledge, in a specific time-frame (Salomon, 1979; Rogers, 1999). Technological landscapes imply a particular social context of shared technological knowledge and may allow us to define areas of interaction.

The set of preliminary assumptions that guide the exploratory analyses conducted may be summarised as follows: (i) the patterning of material culture is a direct result of the social relationships between individuals and groups in which these objects were produced, used and circulated (Coward, 2010); (ii) different mobility capabilities are related to different technological developments; (iii) a set of technological variables may be the most discriminant in order to distinguish between nautical and pedestrian mobility; (iv) sites exhibiting technological features characteristic from both mobility types may indicate interaction areas between nautical and pedestrian populations.

The first approach selected to deeper delve into the possible relationships between mobility and technology consists of implementing different supervised learning classification algorithms. Each classifier uses a different set of assumptions -inductive bias- to generalize beyond the data. To choose the appropriate one, improve accuracy and capture the underlying association patterns between variables, we have compared through stratified 10-fold nested cross-validation (Anderssen et al., 2006; Varma and Simon, 2006) several benchmark and top classification algorithms. These classification algorithms detect on our data significant patterns between mobility types and certain technological elements, traits or knowledges. Afterwards, with the aim of identifying the variables that better discriminate between both mobility types, individual and group variable importance analyses were conducted by implementing diverse state-of-the-art variable importance analysis methodologies.

3.-MATERIAL AND METHODS

3.1.-DATA

To understand the potential relationship between technology and nautical and pedestrian mobility capabilities, we compiled all the available information (more than 250 publications, official reports, and manuscripts) about 201 archaeological sites from Southern Patagonia, collecting spatial, chronological and technological data (Pal et al.).

This large database includes 258 occupations ranging from the Pleistocene-Holocene transition (13000 BP, following (Salemme and Miotti, 2008) to the European colonization in the final period of the XIX century (Gusinde, 1931, 1937, 1974) involving inland and coastal archaeological sites. Within the database, 52,71% of the occupations (n=136) are sites identified as pedestrian by the archaeological literature, i.e., corresponding to HG and HFG groups with pedestrian mobility, while the rest of the occupations (n=122) are identified as nautical, i.e., corresponding to HFG groups with nautical technology.

To increase the sample size, assemblages retrieved from undated deposits were also included in the database. Given the information gathered, ranging from archaeological research conducted in the study area from the 1930's (Bird, 1993) until today, terminological differences had to be overcome to ensure a homogeneous and operational database. All data collected from the papers, books, and manuscripts consulted, was critically reviewed and homogenized under unified criteria. The final database includes technological information about lithics, bone tools and artefacts on shell, considering raw materials, manufacture techniques, design, and decoration. In terms of variables, it comprises 187 variables and frequency data. For the purpose of the present research, the database was normalized into a binary matrix (presence/absence).

The database is focused on the archaeological record of the southernmost portion of South America: from 51ºS until Cape Horn (55ºS), involving inland and coastal environments. The study area includes in the continent, the Austral Magellan Basin, the Andean area, the Pacific and Atlantic Coasts and the Patagonian Steppe. The insular context encompasses the Fuegian Archipelago: a preeminent marine environment formed by a mainland mass, Isla Grande de Tierra del Fuego (IGTDF), surrounded by numerous and minor islands, including Isla de los Estados and Isla Hornos. The selected area is suitable for the aim of the present study, since it involves different landscapes where, according to the geographical localization of the archaeological sites, pedestrian and nautical mobility capabilities can be expected, either inland or near to maritime or lacustrine shorelines.

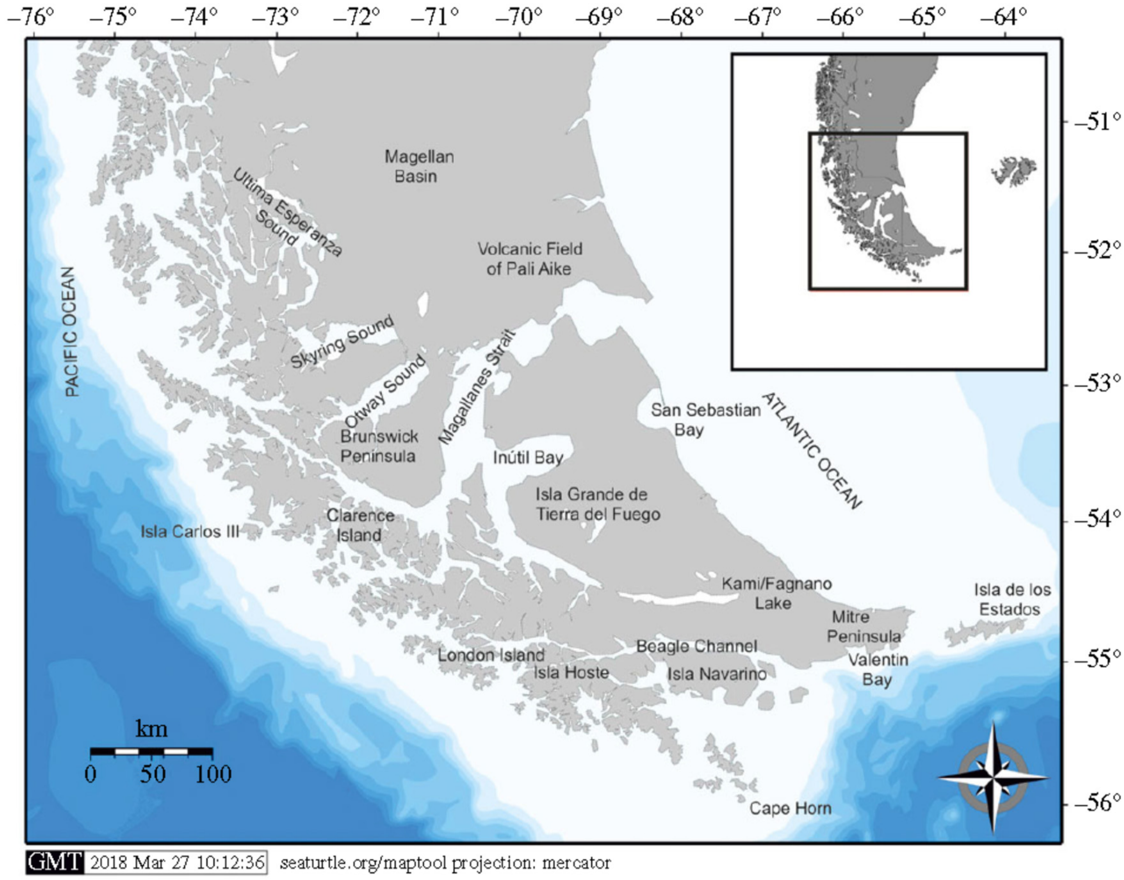


Fig. 4. General map of the study area.

3.2.-CLASSIFICATION TECHNIQUES

Classification is the problem of assigning a new observation to a class among a set of categories or labels. In statistical and machine learning, this assignment is based on the pattern learned from a training set of observations whose label is known (supervised learning). In our case study, we are interested in learning to differentiate between occupations with nautical or pedestrian mobility patterns (labels), based on archaeological technological evidence.

In classification, there is no algorithm that outperforms all the others in all possible cases (Wolpert, 1996); consequently, it is necessary to select the most appropriate classifier for each context. According to recent research, some of the most general cutting-edge classification algorithms include random forest, rotation forest, boosting and support vector machines among others (Fernández-Delgado et al., 2014; Rokach, 2016).

In addition to these classification algorithms, other benchmark classifiers have been implemented to establish a baseline and to check if patterns between the inputs and the output are significant or not.

The set of algorithms considered is the following: random forest, rotation forest (J48 as base learner), AdaBoost (J48 as base learner), support vector machines (SVM) using Gaussian and polynomial kernels, J48 decision tree, naïve Bayes, OneR and ZeroR. Then, the different results were compared, and the model that best fits our data was selected by 10-fold nested cross-validation.

Random Forest is based on the construction of different classification trees on bootstrapped samples of the training set. Apart from bagging (bootstrap aggregation), random forest includes the random subspace method, which consists in forcing each split to consider only a subset of predictors when building a tree; this mechanism helps to decorrelate the different trees built for the same forest (Breiman, 2001).

Rotation Forest was first conceived with the aim of building accurate and diverse classifiers (bias-variance trade-off) (Rodriguez et al., 2006). To create the training data for each base classifier, the feature set is randomly split into K subsets; then, for every such subset, a non-empty subset of classes is randomly selected and a bootstrap sample of size 75 percent of the data count is drawn. Next, Principal Component Analysis (PCA) is run. In the end, a full feature set is reconstructed to build each classifier in the ensemble. Eventually, each item is assigned to a class according to the majority vote calculated over all the trees in the ensemble.

AdaBoost (Schapire, 1990) was the first practical boosting algorithm. However, it remains one of the most widely used, with applications in numerous fields. Boosting aims at creating a highly accurate classifier by combining weak classifiers. In contrast to bagging, which fits a separate decision tree to each bootstrapped copy of the data set and combines all the trees to create a single predictive model, in the case of boosting, trees are grown sequentially, being each tree grown using information from previously grown trees. Instead of implementing bootstrap sampling, in boosting algorithms, each tree is fit on a modified version of the original data set, i.e., the residuals of the previous model, so that the new tree performs better on the points where the previous one performed poorly.

J48 is an open source Java implementation of the C4.5 algorithm in Weka. C4.5 is an algorithm used to generate a decision tree developed by Ross Quinlan (1993). C4.5 splitting criterion is the normalized information gain (difference in entropy). The attribute with the highest normalized information gain is chosen to make the decision.

Support Vector Machines are an extension of the support vector classifier that results from enlarging the feature space using kernels (Cortes and Vapnik, 1995; James et al., 2007). The support vector classifier is based on the construction of a hyperplane such that it correctly separates most of the training observations into two classes. Then, an observation is classified depending on which side of a hyperplane it lies. It is a perfectly valid approach if the boundary between the two classes is linear. Unfortunately, linear boundaries are usually not the case, and that is why in SVMs the feature space is enlarged to accommodate a non-linear boundary between the classes. The kernel approach is simply an efficient computational technique for enacting this idea. Several kernels exist and no-one has proved better than the rest. Therefore, the selection of the kernel type depends on the particular case. In the present work, two different kernels were tried: polynomial kernel and Gaussian kernel, the latter performing better on our data.

Naïve Bayes or Bayes classifier is a very simple probabilistic classifier which is also quite popular due to its good performance in many applications. It assigns each observation to the most likely class, given its predictor values (James et al., 2007). This classifier relies on Bayes' theorem and assumes independence between the features, ignoring any possible correlations between them (naïve assumption).

The last two algorithms, i.e., OneR and ZeroR, are characterized by their lack of predictive power; however, they are useful to establish a baseline performance (benchmark) for other classification methods.

ZeroR is a classification method which relies on the output and ignores all predictors. ZeroR classifier simply predicts the most frequent class, regardless of the predictor values, giving a lower limit on the accuracy (Witten et al., 2011).

OneR (One Rule) is a simple classification algorithm that generates one rule for each predictor in the data set. At a later stage, it selects the rule with the smallest total error and establishes this rule as its "one rule." In some cases, it has been shown that OneR produces rules only slightly less accurate than state-of-the-art classification algorithms while producing rules by far simpler to interpret (Holte, 1993). Therefore, OneR also provides a baseline performance.

3.3.-VARIABLE IMPORTANCE ANALYSIS AND GROUP VARIABLE IMPORTANCE ANALYSIS

Variable importance analysis can be performed both at individual and at aggregated level. In the present work, both analyses have been conducted. Variable importance analysis at individual level has been computed using two main types of measures: model-independent measures (phi coefficient and information gain) and a model-dependent measure (mean decrease in accuracy).

Phi coefficient

The phi coefficient is a measure of association between two binary variables. It is similar to Pearson correlation coefficient in its interpretation. In fact, a Pearson correlation coefficient estimated for two binary variables will return the phi coefficient. It ranges from -1 to 1, where 1 stands for strong positive correlation, -1 for strong negative correlation and 0 for no correlation.

Information gain

Information gain (IG) quantifies the amount of information that an attribute gives about the class using the reduction in the Shannon entropy (22).

$$IG = H(class) - H\left(\frac{class}{attribute}\right) \qquad \textbf{(22)}$$

Entropy is a magnitude that tries to measure how mixed data is with respect to a target variable (i.e. the class to which it belongs in the classification problem). Thus, if all classes are equally represented (maximal mixture), then entropy is maximal and vice versa. Features that are unrelated to the output produce no information gain while features that perfectly partition should give maximal information.

Mean decrease in accuracy

Mean decrease in accuracy is a variable importance measure for ensemble models (such as random forests), based on bootstrapping. The method takes the fitted model, performs a permutation test (Breiman, 2001) and checks its impact on the prediction of the out-of-bag observations (OOB) from a single bootstrapped sample (James et al., 2007). If the variable under consideration is not important, (null hypothesis), then rearranging the values of that variable will not degrade the prediction accuracy and vice versa. Therefore, one can evaluate the importance of a variable by quantifying the change in predictive accuracy after the permutation with respect to the initial case.

3.4.-GROUP VARIABLE IMPORTANCE

In many situations, groups of variables can be naturally identified, and it is of interest to select groups of variables rather than to analyse them individually (He and Yu, 2010). Permutation importance has been recently extended to groups of variables and specifically defined for the particular case of random forests (Gregorutti et al., 2015).

Let $J = (j_1, \cdots, j_k)$ be a k-tuple of increasing indices in $\{1, \cdots, p\}$, with $k \leq p$. The permutation importance of sub-vector $X_J = \left(X_{j1}, X_{j2}, \cdots, X_{jk}\right)^T$ of predictors can be defined as follows (23):

$$II(X_J) = \mathbb{E}\left[\left(Y - f\left(X_{(J)}\right)\right)^2\right] - \mathbb{E}\left[\left(Y - f(X)\right)^2\right] \qquad \textbf{(23)}$$

Where $X_{(J)} = \left(X_1, \cdots, X'_{j1}, X_{j1+1}, \cdots, X'_{j2}, X_{j2+1}, \cdots, X_p\right)^T$ is a random vector such that $X'_J = \left(X'_{j1}, X'_{j2}, \cdots, X'_{jk}\right)^T$ is an independent replicate of X_J which is also independent of Y and all other predictors. It is important to note that the same random permutation is used for each variable X_j of the group. In this way, the (empirical) joint distribution of X_J is left unchanged by the permutation, whereas the link between X_J and Y and the other predictors is broken.

A rescaled measure (24) penalizing the group size can also be defined (Gregorutti et al., 2015):

$$I_{nor}(X_J) = \frac{1}{|J|} I(X_J) \qquad \textbf{(24)}$$

4.-RESULTS.

The analyses conducted in this research yielded three main results: (i) the recognition of the technological sets of nautical and pedestrian groups, (ii) the identification of technological landscapes and (iii) the assessment of social interaction patterns between both types of societies.

4.1.- TECHNOLOGICAL SETS OF NAUTICAL AND PEDESTRIAN GROUPS

4.1.1.-CLASSIFICATION ACCURACY, ANOVA, AND POST-ANOVA

For the present case study, random forest is the technique that best fits our data, with an average accuracy of 86,4%. In the first two columns of Table 1, the average accuracy and the standard error of the classifiers are shown. Results were obtained using stratified 10-fold nested cross-validation. Stratification was chosen to ensure that each fold is a good representative of the whole, i.e., that the proportion of classes in each fold is the same as the proportion in the whole data set.

To assess the robustness of the classification techniques implemented, Anova and post-Anova tests were undertaken. The Anova test was conducted to check the null hypothesis of equality of means across all the algorithms implemented. The result is that the null hypothesis can be rejected at a level of significance of 0.001, which means that the more sophisticated algorithms perform significantly better on our data set than the baseline ones. This implies that some patterns exist between the regressors (technology) and the output (mobility), being RF the technique that best captures those patterns.

To complete the study, a post hoc analysis was conducted by implementing Duncan’s multiple range test for accuracy, with a 0.05 level of significance (Table 1). According to Duncan’s multiple range test, two classifiers are considered statistically different if the accuracy difference exceeds a studentized range statistic. Each classifier is given letters according to the accuracy differences. Differences between classifiers with different letters are considered statistically significant while differences between classifiers that share a letter are not considered statistically significant.

Table 1. Average accuracy and standard error of each classifier. Results were obtained using stratified 10-fold nested cross-validation. The test of equality of means can be rejected at level of significance of 0.001 using an Anova test. Duncan’s multiple range test for accuracy (alpha: 0.05) was used for post hoc analysis. Two classifiers are considered statistically different if the accuracy difference exceeds a studentized range statistic. Differences between classifiers that share a letter in the subgroup are not considered statistically significant.

Classification method	Average accuracy	Standard error	Subgroup
Random Forest	86.446	2.396	A
SVM-Norm. Polynomial kernel	86.046	3.377	A
Rotation Forest (J48 as base learner)	84.908	2.263	Ab
Adaboost (J48 as base learner)	82.584	3.162	Ab
SVM-Gaussian kernel	82.584	3.162	Ab
J48 decision tree	77.200	2.351	B
Naive Bayes	68.523	2.912	C
OneR	59.246	2.742	D
ZeroR	52.708	0.510	D

Since the group variable importance analysis proposed is based on a permutation test conducted on a random forest fitted to the data set, the fact that the model necessary to perform the analysis is the one with the highest accuracy on our data, reinforces the robustness and coherence of the global analysis.

4.1.2.-INDIVIDUAL VARIABLE IMPORTANCE

The results obtained from the individual variable importance analyses performed with both model independent and model dependent measures are coherent. The rankings obtained with each metric are slightly different from each other, but in overall terms, it can be asserted that the great majority of variables happen to be unimportant to discriminate between nautical and pedestrian mobility.

To analyse more in detail the few variables that are discriminant, the variables in the top 20 of the three metrics were considered. In particular, Table 2 shows the 19 most important variables, arranged according to the number of metrics in which those variables are part of the top 20: 3 metrics out of 3 and 2 metrics out of 3.

Table 2. Ranking of the 19 most discriminant variables for mobility patterns according to the individual variable importance analyses. In the table, we show the variables which are discriminant according to 3 out of 3 and 2 out of 3 metrics. The

grey-shadowed variables are the variables that point to pedestrian mobility. The variables in white point to nautical mobility.

Top 20		Ranking	Information Gain	Ranking	Phi coefficient	Ranking	MDA
3/3	Vulcanites	1	0,0938	1	0,31429	8	12,0644
	Magallanes IV point	2	0,0798	4	0,28193	7	12,9218
	Shell beads	3	0,0749	5	0,28042	16	8,9450
	Siliceous rocks	4	0,0717	2	0,29299	3	14,3780
	Awl	5	0,0628	3	0,29014	13	10,4073
	Black obsidian	6	0,0599	8	0,24354	10	11,2958
	Chalcedony	7	0,0591	6	0,26975	1	17,0914
	Rhyolites	9	0,0464	7	0,25252	4	13,6742
	Multi-barbed harpoon	10	0,0456	9	0,23825	20	7,6720
	Cinerite	12	0,0418	10	0,23416	19	7,6994
	Bone pounder	14	0,0355	15	0,20214	17	8,1364
	Basaltic rocks	16	0,035	13	0,21621	6	12,9606
2/3	Splinter with traces	8	0,0476	11	0,22281		
	Chisel	11	0,0431	14	0,21201		
	Simple shoulder harpoon	13	0,0378	12	0,21783		
	Bola with groove	15	0,0355	16	0,20214		
	Pecked notched pebbles	17	0,0343	19	0,18887		
	Decorated harpoon	18	0,0343	20	0,18887		
	Sharpened object	19	0,0303	18	0,19597		

According to the results presented in Table 2, the key discriminant variables include technological features related to some specific lithic and bone tool designs, together with lithic raw materials. Important diagnostic features for pedestrians are the projectile point known in the classical Archaeology of southern Patagonia as “Magallanes IV” (Bird, 1993), bone pounders and bolas with grooves. Nonetheless, it is necessary to clarify that in the archaeological record the last two designs also appear in two different nautical sites of the Magellan Strait area.

Conversely, shell beads, a series of bone tools and pecked notched pebbles are salient technological characteristics of nautical societies. Shell beads, multi-barbed and decorated harpoons, splinters and chisels are limited to nautical occupations. On the contrary, awls, simple shoulder harpoons and sharpened objects were also used by pedestrian groups.

With regard to raw materials, the number of variables involved in their exploitation, such as geographical distribution, accessibility, the problems related to source identification and the biases related to the classification criteria used by different analysts, make it difficult to provide straightforward explanations. The procurement of rocks at available local sources nearby the archaeological sites partially explained the strong association between raw materials and mobility. This applies to basalts, chalcedonies and siliceous rocks linked to pedestrian mobility, as well as to rhyolites, vulcanites and cinerites associated with nautical groups. However, most of these raw materials are found in both groups since they present a relative ubiquitous distribution in secondary deposits, having been transported by the action of glacial and glaciofluvial processes during the Quaternary. Consequently, the presence of these rocks in the archaeological record does not necessarily imply inter-group connectedness.

The opposite is the case of black obsidian, whose geological region of provenance has been identified (Stern, 2004); it is located in Pampa del Asador, around 47° 50´ 17´´ lat. S and 70° 59´ 11´´long W, circa 400 km away to the North from the study area. This type of obsidian, exclusively associated with pedestrian societies, is distributed along the occupations of the continent but it also appears in Marazzi I, a site located in the IGTDF steppe (more than 600 km away from the source) after the opening of the Magellan Strait. Contrastingly, the other two raw materials available in primary sources in the study area, green obsidian and Miraflores rocks, follow a dissimilar pattern and exhibit a relatively wide distribution between nautical and terrestrial groups (Morello et al., 2012; Borrazzo et al., 2015). The source of green obsidian is located around Otway Sound, and the source of Miraflores rocks (tuffs and silicified tuffs) is situated in the Chorrillo Valley in the north of IGTDF. As the vast majority of the territory in Otway Sound was occupied by maritime societies, it has been suggested that green obsidian was distributed and controlled by these groups. On the contrary, terrestrial hunter-gatherers controlled the circulation of Miraflores rocks throughout IGTDF (Pallo and Borrazzo, 2016).

4.1.3.-GROUP VARIABLE IMPORTANCE

Nine main aggregated categories have been considered since the 187 predictive variables can be accurately partitioned into them: raw materials, techniques, bone tools, point designs, scrapers, polished/pecking, side-scrapers design, ornaments, and decoration. These nine groups happen to be of interest, mainly because of their synthesis capability. The results obtained can be seen in Fig. 5.

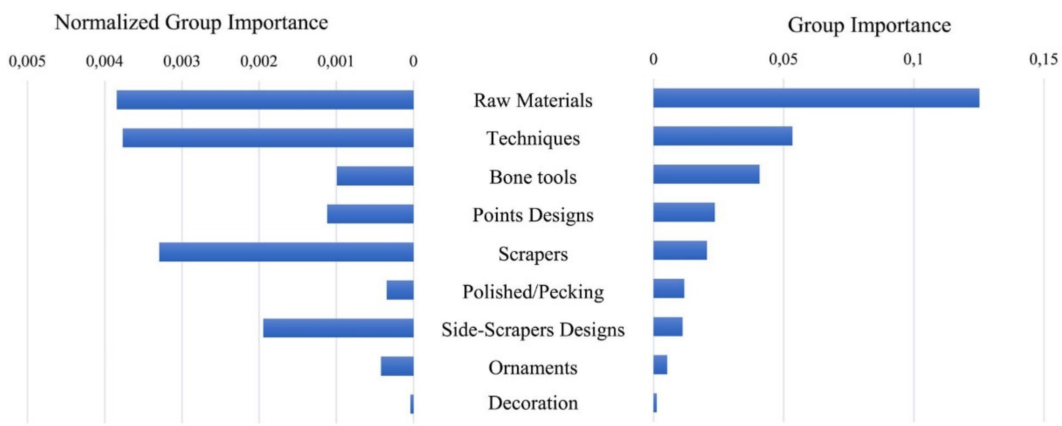


Fig. 5. Group importance and normalized group importance of the nine groups of variables used as regressors.

Two different group variable importance analyses were conducted: one without normalization of the variables and the other in accordance with the normalization procedure by Gregorutti et al. (2015), which divides by group size. Since the most suitable normalization procedure for group variable importance analysis is still to be determined, the values obtained with Gregorutti's normalization are just presented as complementary information. It is the ranking given by the group variable importance analysis without normalization that is studied and analysed in detail.

Putting aside raw materials (because of the problems mentioned above related to their distribution and source identification), several interesting archaeological results arise from the analysis of the results in Fig. 5:

First, the group of techniques, which comprises different ways in which force was applied to produce an object, is more diagnostic than artefact morphologies. Second, bone tools and projectile points remain important. Third, in contrast to individual variable importance analysis, group variable importance points to scrapers and side-scraper designs as having a non-negligible significance to distinguish between mobility types. Fourth, interestingly, ornaments and decoration, which are commonly used in Archaeology as diagnostic traits for identifying groups, appear at the end of the ranking, being consequently the least significant groups to distinguish between nautical and pedestrian mobility types. At this point, it is important to note that decorated items exhibit lower frequencies in the archaeological record in comparison to the rest of technological variables, which may have some kind of influence in the results obtained.

5.-DISCUSSION

5.1.- TECHNOLOGICAL LANDSCAPES

In archaeological research, the traditional procedure for identifying technological interaction consists of the analysis of the spatial connectedness of technological variables. In contrast, in the present study, the technological landscapes have been obtained by geo-positioning the sites classified as nautical or pedestrian by the random forest algorithm and by checking the classification obtained against the archaeological literature. This new methodology, aside from the representation of technological landscapes, enables the identification of the boundaries between them and, more importantly, the detection and analysis of conflictive points, possible indicators of interaction between groups. The geographical distribution of the sites classified as nautical by the random forest, encompasses a technological landscape which involves two areas: the coastlines of Otway-Skyring Sounds, and the Beagle Channel-Valentín Bay area. Some sites included in this technological landscape are placed in the Westernmost section of Magallanes Strait, including Port Famine and the vicinity of Isla Carlos III. The absence of archaeological sites in the South-Western Channels (Clarence Island, London Island and IGTDF, among others) can be easily explained by the absence of archaeological research in this area.

This space of shared technology is not merely linked to marine ecosystems; it is related to a landscape of channels, islands, and watercourses where seafaring technology was indispensable. In addition, it is interesting to note that there is no evidence of the use of nautical technology in HG societies of the Atlantic coast of IGTDF and Continental Patagonia: the relationship between seafaring and technological variability is strongly related to the Pacific Coast. One of the most relevant results obtained is that the geographical pattern of the nautical technological landscape supports the hypothesis of the arrival of nautical societies to Magellan-Fuegian Archipelago, in the Middle Holocene, through the Western Channels and Islands of the Pacific Ocean (Legoupil and Fontugne, 1997; Ocampo and Rivas, 2004).

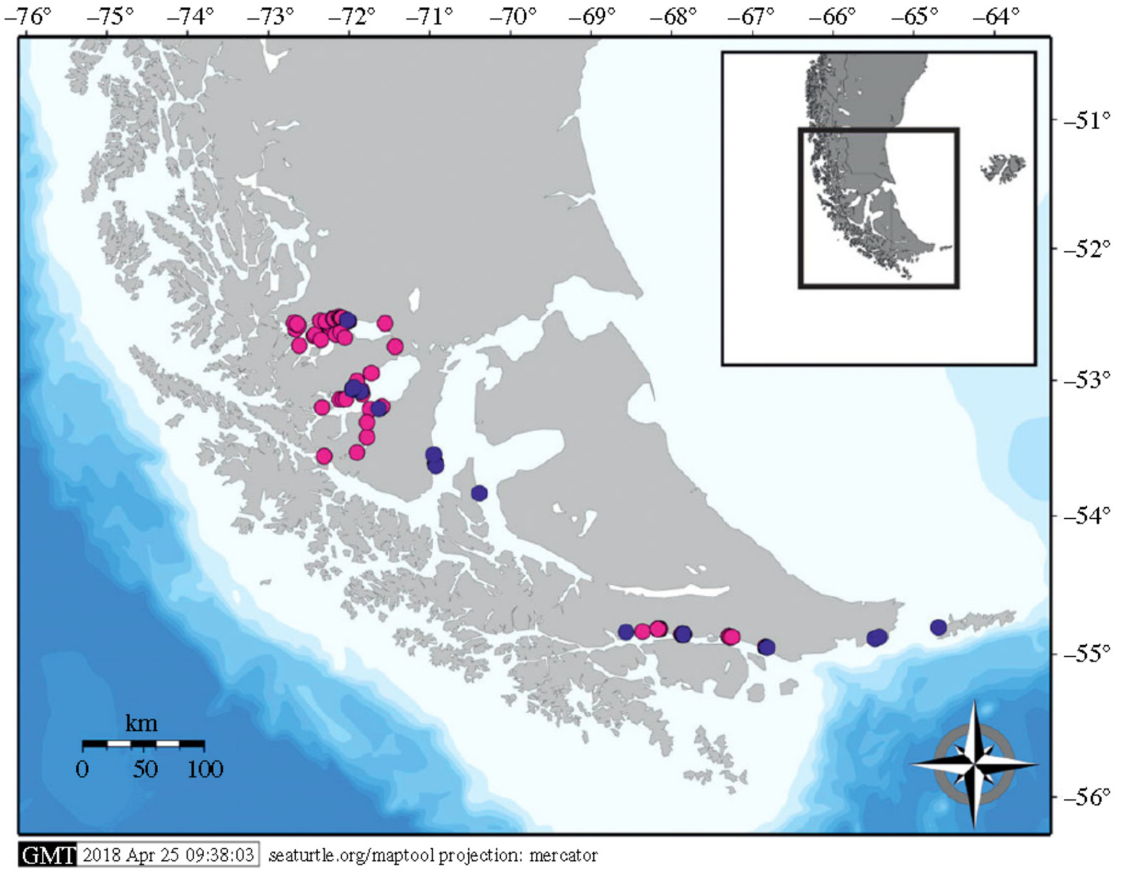


Fig. 6. Map with nautical occupations. Blue dots are misclassified by the algorithm, i.e., the classifier predicts that the blue dots are pedestrian occupations, whilist in reality they are nautical; red dots are classified in coherence with the archaeological literature.

In the case of sites classified as pedestrian by the random forest algorithm, the technological landscape obtained presents a geographical distribution which is broader and more homogeneous than the nautical one, covering both inland and coastal areas. Some different concentration areas, with different sizes are present in the study area.

Aggregation areas of pedestrian sites can be observed in the continent, in Última Esperanza Sound area and, especially, in the area of the Volcanic field of Pali Aike and the Río Gallegos Basin. Coastal locations are placed, also, throughout the Atlantic Ocean and the northern shore of the Magallanes Strait. In the case of IGTDF, an important concentration area is placed in the North of the Island, comprising the coasts of San Sebastián Bay and Inútil Bay. The rest of the sites are distributed in inland and coastal landscapes, including the Beagle Channel, Atlantic Façade, and the Khami Lake. The presence of pedestrian sites in the Western and Southern channels is really low, and they are associated with the initial occupation of the Beagle Channel region (Orquera, Luis and Piana, 1999). The existence of a common technological landscape involving the Continent and IGTDF is strongly related to the maintenance and development of technological practices related to the glacial period when the island was a portion of the continent, what enabled the arrival of human groups to the area.

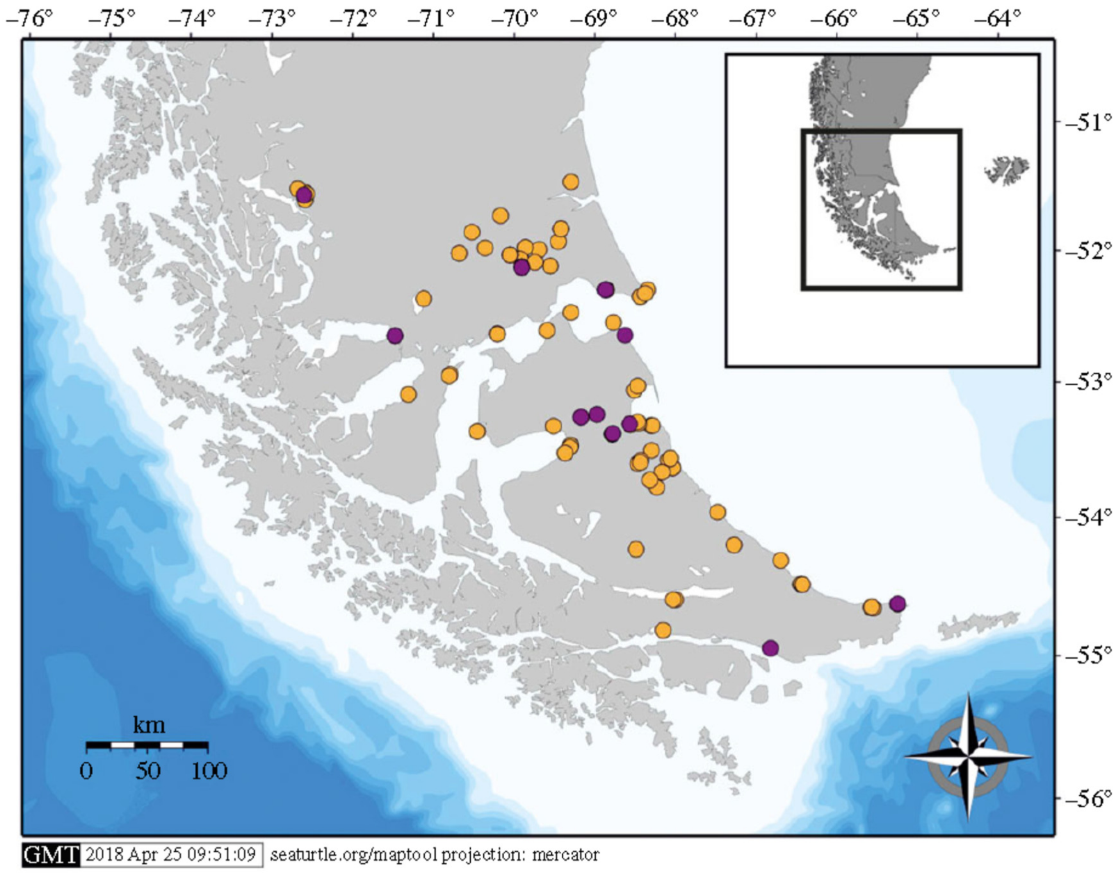


Fig. 7. Map with pedestrian occupations. Green points are misclassified by the algorithm as nautical, even though they are pedestrian, orange points are classified in coherence with the archaeological literature.

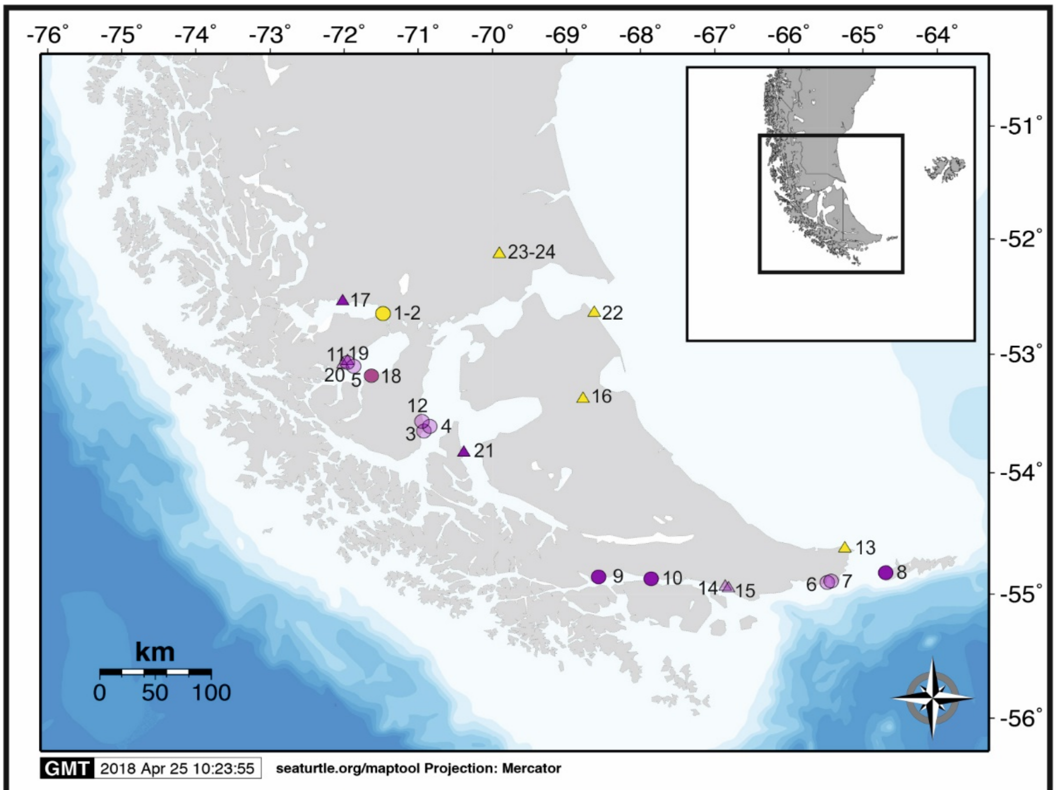
5.2.-SOCIAL INTERACTION

5.2.1.-MISCLASSIFIED CASES

The third main outcome of the analyses conducted is related to the occupations misclassified by the random forest algorithm: up to 24 cases. These misclassified sites are entries that do not follow the general pattern identified by the classification algorithm, which leads the latter to misclassify them. This behaviour reveals entries that need to be studied carefully, to understand the particularities of each case. In overall terms, two main reasons account for these misclassifications: first, the low frequencies of technological materials retrieved from these sites and/or the scarcity of data provided by publications;

this situation encompasses 50% (n=12) of the misclassified occupations, which are distributed in many different areas. Consequently, this outcome is not linked to a specific time-frame or excavation/analysis method.

Second, the existence of a group of misclassified sites which cannot be accurately classified into nautical or pedestrian, since in their records distinctive technological variables are scarce or absent and/or because they exhibit technological features from both nautical and pedestrian assemblages. Henceforth, these misclassified sites could be considered proxies of connectivity and interaction between nautical and pedestrian communities. (Fig. 8). Most of the misclassified points in this second group are located in places of easy access between inland and marine landscapes, thus fostering communications among HG/HFG societies. Incidentally, the biggest aggregation of sites (n=7) in this second group is scattered around the Otway Sound and the Magellan Strait, which has been traditionally pointed as an area of contact between nautical and pedestrian societies by ethnographical sources (Gusinde, 1974). The same occurs with the assemblages of Mitre Peninsula (n=2). In the case of Beagle Channel (n=2), even though it has been considered a territory of nautical populations, the establishment of connections with Otway and Brunswick Peninsula is well documented by ethnography and ethnohistory (Schidlowsky, 1999; Álvarez, 2004; Fiore, 2006).



INTERACTION	LACK OF INFORMATION
1-Ponsonby *locus* 1	13-Aleph 1
2-Ponsonby *locus* 2 (Level of crete)	14-Heshkaia 30
3-Punta Santa Ana 2	15-Heshkaia 34
4-Punta Santa Ana 3	16-Tres Arroyos 14-88
5-Pizzulic 3	17-Skyring 35
6-Bahía Valentín 11 (Level 2)	18-Candem 2
7-Bahía Valentín 42	19-Caleta Eros 1
8-Bahía Crossley	20-Caleta Eros 2
9-Isla El Salmón	21-Offing 2
10-Shamakush burial	22-Espíritu Santo 1
11-Los Noruegos	23-Pali Aike 1 (Level 3)
12-Km 44	24-Pali Aike 1 (Level 5)

Fig. 8. Misclassified points. Misclassified nautical points in purple, misclassified pedestrian points in yellow. Circles are misclassified points due to interaction. Triangles are misclassified points due to lack of information. In the bottom table, 12 sites misclassified by the random forest classifier: we can see the name of the occupation, the classification of the site according to archaeological literature and the classification provided by the random forest algorithm.

In a nutshell, these results highlight the existence of networks of technological knowledge related to mobility patterns. This technological knowledge was transmitted and exchanged among the members of each society and between societies, being particularly interesting the interaction points between the two mobility trends, i.e., the sites where both nautical and pedestrian technologies can be found, which leads the algorithm to misclassify them.

6.-CONCLUSIONS

The present paper provides relevant insights to understand the relationships between shared technology and mobility patterns in pedestrian and nautical HG/HFG societies.

A formal approach has been used to detect patterns of shared technology and to identify the variables which are more relevant to discriminate mobility. In this sense, we draw on a comprehensive database, which encompasses a wide range of technical features considered as material proxies, to identify interactions and social boundaries.

The analyses presented here demonstrate, first, that there is a strong and non-trivial dependence between technology and mobility patterns, being the relation based on a restricted number of technological items. This result suggests that the study area was highly integrated through the circulation of knowledge and/or a variety of materials, since most of the technological evidence is shared by all the HG/HFG societies in the region. But, at the same time, it highlights that these networks implied a heterogeneous circulation of technological knowledge among groups, in terms of manufacturing techniques, material objects and their geographical distribution. Furthermore, at a higher level of abstraction, the outcomes of group variable importance acknowledge which are the most significant proxies to distinguish mobility strategies, thus providing a hierarchy, and broadening the spectrum of technological variables that could be explored to assess people connectedness.

In this sense, the methodological approach adopted here undercuts basic assumptions supported by archaeologists, regarding the identification of exceptional diagnostic features to establish social ties or boundaries between groups. Conversely, we propose to analyse technology “in action”, which involves a deep comprehension of how tools are produced and used by individuals and societies. The predictive models obtained using comprehensive technological assemblages improve the accuracy beyond that of direct classification based on decision trees, “index fossils” or decorative styles. Therefore, and in accordance with the results provided by the group variable analysis conducted, we can emphasise the importance of the processes underlying the production of artefacts as reliable archaeological markers of both technological development and social interaction. An approach based on the technological processes needed to obtain the artefacts enables to overcome two common arguments in archaeological research related to the difficulty in establishing connectedness between groups based on the final lithic artefacts: (i) that their design responds to functional requirements and (ii) that there are certain morphologies which are distributed worldwide. It is highly recommendable that future research devotes special attention to the processes underlying the production of artefacts as opposed to the shape of the artefact, which in accordance with our findings may not be the most distinctive trait.

Secondly, the classifiers implemented allow to identify the geographical areas where significant social interactions could have taken place, (for example Otway-Skyring Sounds) as well as to distinguish regions with rather weak connections. This information, coming from the misclassified archaeological occupations, has been used to analyse in detail potential salient regions, detecting, in some cases, interaction areas or places with absence of evidence. Further research will be addressed to assess the existence of geographical or social barriers which could have hindered the spread of technological knowledge.

The example of the present case study stresses the potential of exploring standardized and formalized broad-spectrum databases with advanced machine learning and statistical tools, since the models and conclusions obtained can serve as decision support tools and as analysis guide, not just for the present case, but the whole archaeological discipline.

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DATA ACCESSIBILITY STATEMENT.

Bibliography and reports used to generate original database are available in:

https://www.researchgate.net/publication/324217985_Reference_Database_of_Hunter-Gatherer_Technology_from_the_uttermost_tip_of_Patagonia_South_America

(DOI: 10.13140/RG.2.2.11121.79202).

Specific Database used in the statistical analysis is included in the paper as ESM

4. ROBUSTNESS ASSESSMENT OF THE COOPERATION UNDER RESOURCE PRESSURE MODEL (CURP): INSIGHTS ON RESOURCE AVAILABILITY AND SHARING PRACTICES AMONG HUNTER-GATHERERS

Debora Zurro, Virginia Ahedo, María Pereda, Myrian Álvarez, Ivan Briz i Godino, Jorge Caro, José Ignacio Santos, José Manuel Galán

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ABSTRACT

A well-known challenge in archaeological research is the exploration of the social mechanisms that hunter-gatherers may have implemented throughout history to deal with changes in resource availability. The agent-based model (ABM) Cooperation Under Resource Pressure (CURP) was conceived to explore food stress episodes in societies lacking a food preservation technology. It was particularly aimed at understanding how cooperative behaviours in the form of food sharing practices emerge, increase and may become the prevailing strategy in relation to changes in resource availability and expectancy of reciprocity. CURP's main outcome is the identification of three regimes of behaviour depending on the stress level. In this work, the model's robustness to the original selection mechanism (random tournament) is assessed, as different dynamics can lead to different persistent regimes. For that purpose, other three selection mechanisms are implemented and evaluated, to identify the prevailing states of the system. Results show that the three regimes are robust irrespective of the analysed dynamics. We consequently examine more in detail the long-term archaeological implications that these results may have.

1. INTRODUCTION

Natural resources and their distribution are paramount for understanding life at different scales. Regarding the human species, the role played by resources is even more significant, as resource availability is also the material basis upon which any social behaviour or strategy emerges and evolves over time. The resource exploitation strategies implemented by human societies constitute a transversal topic of interest for many research fields. In particular, the paradigm known as Human Behavioural Ecology-HBE (Nettle et al., 2013) addresses in the form of archaeological studies not only functional explanations linked to carrying capacities, resource exploitation, productive aspects including technology and consumption or mobility and reproductive strategies, but also historical ones, related to the origins of agriculture, intensification and colonization processes, among others (see a review in Bird and O'Connell (2006)).

Within the most common archaeological discourse, it is often assumed that whenever resources become scarce for the existing population, human societies tend to modulate this unbalance between population and resources through changes in the production/consumption sphere. These changes might include different strategies ranging from risk minimization (Smith, 1972; Minc and Smith, 1989; White et al., 2011; Zeder, 2012; Ryan and Rosen, 2016) to changes in demographic dynamics (Speth, 2004; Williams et al., 2015). However, due to the intrinsic nature of Archaeology, which deals mainly with material remains, it is not straightforward to reconstruct the social domain and the food distribution patterns through them (Enloe, 2003). Consequently, several archaeological studies have focused on very specific examples such as the study of the development of trade and interchange systems (Dyke, 1999; Chapman, 2008) or the study of (communal) storage structures or technologies (see a review in (Angourakis et al., 2015)).

Leaving aside the archaeological limitations due to its materiality, we know from Ethnography, Ethnoarchaeology, and Ethnohistory that hunter-gatherer (HG) societies use not only specific technologies but also social organizational measures to deal with the different scenarios produced by the heterogeneous temporal and spatial distribution of resources. Good examples of social organisational measures among HG are mobility, aggregation, and fission dynamics, which are included in Binford's packing model (Binford, 2001). Another particularly relevant social measure is sharing, a complex phenomenon around which several debates regarding its economic and social function continue to exist. Sharing appears in diverse contexts where it can be explained in pursuit of different objectives ranging from showing the own reproductive potential to sheer survival. In the present study, we focus on the facet of food sharing that allows dealing with future possible subsistence instability through indirect reciprocity; the surplus is shared with other community members in the hope that they will do the same in the future ((Winterhalder, 1986; Bird, 1997; Borgerhoff Mulder and Schacht, 2012) among others).

From all the above, it appears clear that to understand the complexity of social dynamics beyond material remains and ethnographic narratives, simulation tools such as Agent-Based Modelling (ABM) provide a good framework for the exploration and analysis of social contexts.

ABM allows expanding our frames of reference for several issues that range from the very empirical to theoretical matters, as it offers the possibility to move from the micro to the macro scale studying emergent properties. In this sense, modelling becomes a theory building tool (Verhagen and Whitley, 2012; Whitley, 2016) in which, when going back to reality, it is extremely important to extend the conclusions of the model in accordance with the aim for which it was developed, as different models can be built for different purposes: generating theory, prediction, classification, etc., and its conclusions should not be extrapolated elsewhere.

ABM models work towards improving the Social Sciences in general engendering debates about new paradigms within the framework of what has been called generative social science (Epstein, 1999).

When linked together with Ethnography and Ethnoarchaeology, ABM models based on ethnographical knowledge allow exploring how societies behave in relation to resources (if they are shared and how) once they have been acquired. It is worth noting that the variety of variables necessary to understand social mechanisms makes computer simulation particularly suitable for their analysis, as modelling allows generating multiple environmental scenarios on variable spatial and temporal scales (Rautman, 1993; Morrison and Addison, 2008), see Lake (2014) for a review of social simulation in archaeological studies.

Even though social simulation is not yet considered a mainstream approach in Archaeology (Whitley, 2016), its application is increasing exponentially (Wurzer et al., 2015), and there already exist good examples of the use of ABM to address not only resource management (see Freeman and Anderies (2012) and references therein) but also other social phenomena such as cooperation.

Previous research on cooperation and HG societies has dealt with specific topics like cooperative breeding (Smaldino et al., 2013) or cooperative strategies for the sake of production, being cooperative hunting the most relevant example (Stiner et al., 2009).

Other research pieces in the field have focused on specific ethnographic case studies, such as those devoted to the Ache (Janssen and Hill, 2014) and the Maasai (Aktipis et al., 2011), or on sharing phenomena of other resources aside from food, such as territories (Freeman and Anderies, 2012).

The model of cooperation and punishment by Bowles and Gintis (2004) is also aimed at explaining collective phenomena such as food sharing and defense. Particularly, it suggests that cooperative behaviours may well be sustained thanks to strong reciprocity since even if it is an individual behaviour that coexists with other distinct behavioural patterns, it produces a social dynamic and has benefits at the social level.

In the light of the above, we aim to explore how social mechanisms regarding food sharing practices (reciprocity) change in relation to variation in resource availability (subsistence stability and instability). Specifically, we are interested in the conditions allowing the emergence of sharing and its maintenance, as well as in the scenarios that would promote its disappearance.

For this reason, we designed the CURP model, an ABM specifically conceived to offer some insights into how HG societies lacking food preservation technologies may face changing resource availability through social mechanisms of resource redistribution (Pereda et al., 2017a). As it has already been stated, both cooperation and sharing are complex phenomena which can be analysed from different perspectives. However, both in CURP and in this paper, cooperation is modelled just as food sharing.

Agent-based simulation models have been argued to work as theoretical experiments (Edmonds and Hales, 2005) which can help to formally illustrate the implications of a particular set of assumptions in a specific context under study (for instance, in the context of the social phenomena). Although a simulation result can be understood as a valid sufficiency theorem (Axtell, 2000), it is not easy to infer from just a set of simulations if the results are a consequence of the model core set of assumptions or if they are caused by accessory aspects (Galán et al., 2009, 2013). This is particularly important when simulation is used as a tool for the analysis and interpretation of social phenomena, since the ABM used is just a particular instance of a more abstract conceptual model, which could be implemented in different equivalent ways, all of them valid in principle, but whose different dynamics can lead to different stable regimes of the system (Galán and Izquierdo, 2005). Therefore, in this work, we delve further into the CURP model and check the robustness of its results to the evolutionary mechanisms (how individuals share resources and with whom). Similarly to previous social simulation research (Edmonds and Hales, 2005; Galán and Izquierdo, 2005), we use several evolutionary selection mechanisms –all of them compatible with the original conceptual idea– to better understand how wide is the range of applicability of the conclusions of the CURP model, and to try to identify which aspects are consequence of the particular dynamic and which results are robust to the specific adaptive mechanism (persistent regimes of the system). Hence, the aim is to find the prevailing stable areas of the system (once the transient period is over and the initial dynamics do not influence the dynamics anymore), in order to conduct a detailed interpretation of the results in the context of HG, based on those persistent regimes found and not on the specific dynamics to reach them.

2. THE CURP AGENT-BASED MODEL

2.1 DESCRIPTION OF THE MODEL

The CURP model was built in NetLogo (Wilensky, 1999) under the framework of evolutionary game theory and inspired by the hypothesis that a decrease in resources would promote cooperation in terms of food sharing whenever reciprocity is possible, but once resource scarcity reaches a given threshold and reciprocity is less probable, cooperation may become a non-satisfactory strategy. The EGT framework used in this paper not only can be interpreted by natural selection models but also other decision models driven by a gradual change, in which the strategies that are more successful at a given moment are more likely to persist in the future (Sandholm, 2010; Izquierdo et al., 2012).

Here we succinctly depict the core dynamics of the model and detail the assessment of the model’s robustness to the evolutionary mechanisms, which is one of the main contributions of the present work. For further details on the singularities of CURP, please refer to Pereda et al (2017b) or directly to the model, (available at openABM; https://www.openabm.org/model/5287/).

In CURP, resource pressure is modelled stochastically using two different parameters: (i) *prob-resource* (the probability of acquiring resources) and (ii) *min-energy* (the minimal proportion of the resource unit each agent needs to survive).

The model was designed as an artificial society of *N* agents, each one of them defined by three state variables: *given-energy*, *correlation*, and *fitness*, being *given-energy* and *correlation* the variables that define the agent's strategy.

Given-energy is the proportion of the resource unit that the agent under consideration wills to share. *Correlation* establishes the probability of choosing a donee among the set of possible donees, an agent with *correlation* 1 will choose the most previously cooperative individual and one with *correlation* -1 the least cooperative.

Fitness is defined as the number of time periods in which the energy obtained by the agent was greater than *min-energy*, since the conventional definition of fitness intending to maximize the expected resources may not be the most suitable for HG without food preservation techniques. This particular definition of fitness, which dissociates the resources obtained by the agents from the payoffs (and implicitly assumes diminishing marginal returns), makes the CURP model and its conclusions only applicable to societies without food preservation technologies.

Each simulation scenario is defined by the study parameters (see Table 3), which are exogenous variables established by the user that remain constant in each run.

Table 3. Study parameters for each simulation scenario in the CURP model.

Parameter	Description
N-people	The number of agents.
Prob-resource	The probability that an agent obtains a resource unit at each time period.
Min-energy	The minimal proportion of the resource necessary for survival.
Sharing-tournament-size	percentage of agents from the population that obtained no resource at a time period and that are susceptible of being chosen by a particular donor.
Strategy-tournament-size	percentage of agents from the population that a particular agent takes into account for selecting a new strategy. The agent samples strategy-tournament-size agents from the population and then she imitates the best strategy, i.e., the strategy of the agent with the highest fitness if the corresponding fitness is greater than her own.
Prob-mutation	The probability that an agent decides to follow a new strategy randomly chosen from the strategy space.

Rounds-per-generation	Number of time periods for which the values of the parameters that define each agent's strategy remain unchanged. Agents can change their strategy every rounds-per-generation time periods.

The procedure is the following: in each time period, each agent draws resources and gets a unit of energy with a probability equal to *prob-resource*. Then, each agent that succeeded and obtained resources shares them in two steps. First, it selects a donee from a set of the population of size *sharing-tournament-size*, constituted by agents who did not get resources (by themselves or from other donors). The selection of a donee from this set is done according to the value of the agent's *correlation*. Second, she gives the selected donee a *given-energy* proportion of the unit of energy she has. It is important to note that the proportion of energy shared by a donor (*given-energy*) is not conditioned by the *min-energy* survival threshold, which implies that the donor can end up with less energy than the minimum necessary for her own survival.

No donee will receive any more energy from other donors if she gets more energy than the survival threshold established by *min-energy*.

Finally, at the end of each time period, each agent's *fitness*, i.e., the number of non-starving periods, is updated. The *fitness* value increases by a unit if the agent has more energy than the *min-energy* survival threshold.

This process of acquiring and sharing resources with the subsequent update of *fitness* is repeated *rounds-per-generation* time periods. Once the model has run *rounds-per-generation* times, each agent updates her strategy by changing the values of her *correlation* and *given-energy* variables as follows: first she samples *strategy-tournament-size* people agents of the population and then she imitates the strategy with the highest *fitness* if it is greater than hers, unless it is affected by the *prob-mutation* probability, in which case she randomly chooses a strategy from the strategy space.

Pereda et al (2017b) proved using statistical learning analysis that the results of the model depend mainly on two parameters: prob-resource and min-energy, the two variables which define resource pressure. Consequently, to understand the system dynamics and to study the emergence of cooperation and indirect reciprocity via simulation, the two-study parameters *prob-resource* and *min-energy* were evenly sampled over the range [0.2, 0.8] in steps of 0.1, to fully map the outcome space of the model (the details of the parametrisation can be found in Pereda et al (2017b)). Again, each parametrisation was run 5×10^3 generations, being replicated 100 times.

2.2 CURP PREVIOUS RESULTS

Hunter-gatherer societies implement a wide variety of strategies that change according to the different socio-ecological contexts they face. In the CURP model, the different settings are characterized by distinct population volumes and by specific distributions and concentrations of resources, the latter being reproduced through the parametrization of both the probability of finding resources as well as the need of a specific amount of energy for survival. Therefore, the model sheds light on the social realm, enlightening the underlying patterns behind the emergence of two particular social behaviours: cooperation in terms of food sharing and indirect reciprocity.

In HG societies, food sharing is a specific form of cooperation which, when implemented, helps to deal with mid-stress scenarios, where it constitutes a mechanism both to face future risks of food scarcity and to manage food surplus. At the same time, cooperative strategies enhance the emergence of social links that reinforce both sharing practices and other communal behaviours (Briz i Godino et al., 2014).

The first study of CURP showed that after the initial transitory dynamics, three different persistent regimes could be identified: low-stress regime, intermediate-stress regime and high-stress regime. Along these regimes, the emergence and disappearance of cooperative behaviours is the most relevant trend, which shows how cooperation (food sharing) depends both on changes on the possibility to survive (changes in *N-people* and *min-energy*) as well as on the expectancy of reciprocity (*correlation* and *given-energy*).

The three persistent regimes identified by Pereda et al. are:

1. **Low-stress regime** (low values of *min-energy* and high values of *prob-resource*): Under these circumstances, different strategies produce maximum fitness. Survival is therefore very likely. Consequently, changes in the strategy space are driven by random drift. Strategy selection is not important and the average strategic behaviour of the population remains at almost constant values.
2. **High-stress regime** (high values of *min-energy* and low values of *prob-resource*): Very unstable behaviour is the main characteristic of this regime. The high threshold of *min-energy* and the scarcity of resources promote the emergence of low-given strategies. At the same time, new strategies to ensure survival are permanently explored by the agents, mainly because no situation is satisfactory enough.
3. **Intermediate-stress regime**: In this regime, cooperation and indirect reciprocity emerge. Strategies characterise by retaining the resources strictly necessary for survival and giving the rest to the population in a structured manner, since strategies of positive correlation are favoured (the agents that gave more are the ones that receive the most). Consequently, it can be asserted that the population self-organises in an indirect-reciprocity system in which the norm is to share what is not necessary for survival, with the expectancy that the rest of the population will do the same in the future (indirect reciprocity implies that one cooperates with individuals who did cooperate with other members of the population in previous stages, and whose reputation is therefore positive). Thanks to cooperation sustained through indirect reciprocity, the probability of communal survival is significantly increased at a population scale and the probability of being behind the threshold is collectively reduced.

3. METHODOLOGY

3.1 EVALUATION OF THE ROBUSTNESS OF THE MODEL TO THE SELECTION MECHANISM

In some models it can be difficult to faithfully represent the real dynamics of the system under consideration, since the dynamics can be unknown, unobservable, or simply different to the ones we are considering. This motivates the use of plausible hypothesized mechanisms that could have been at work to analyse the stability areas of the system (and not so the transient dynamics), since the system could reach different persistent regimes depending on the particular dynamics imposed (Galán and Izquierdo, 2005).

To test the conclusions obtained from the CURP model and to gain confidence in the robustness of the three regimes initially identified, here we explore the impact on the results of different selection mechanisms. More specifically, the selection mechanism used in the original paper, i.e., random tournament, is compared to other three mechanisms: roulette wheel (due its popularity (Mitchell, 1996)), and two truncation and threshold selection algorithms (Lynch and Walsh, 1998): standard deviation and average selection; this last two mechanisms have been used in some of the most influential works in game theoretic social simulation about cooperation (Axelrod, 1986; Takahashi, 2000), and it has been proved that they can lead to different persistent regimes in comparison to other evolutionary mechanisms (Galán and Izquierdo, 2005). The aim of this comparison is to check if the three regimes appear irrespective of the selection mechanism i.e., that the system tends to them regardless of the internal dynamics imposed.

The selection of strategies happens every *rounds-per-generation* time periods. In the original model (Pereda et al., 2017b), the strategy selection process follows a random tournament: each agent chooses a random sample of other agents and imitates the best strategy, i.e., the strategy of the agent with the highest *fitness* in the sample; at the same time, she randomly chooses a strategy between the strategy space with a probability equal to a mutation parameter. One of the reasons for this approach is that both selection and mutation can be easily interpreted as social imitation and individual exploration, i.e. people usually tend to imitate the best behaviour, although they occasionally explore new alternatives.

In the present work, the three new selection mechanisms, i.e. roulette wheel, standard deviation and average selection have been implemented without changing the mutation process with respect to the original design. In the new mechanisms, just after *rounds-per-generation* time periods, the old generation of agents is replaced by a new one composed by replications of some of the old agents, chosen according to the specific selection mechanisms.

In the roulette wheel mechanism, agents are given a replication probability directly proportional to their *fitness* in the current population. Then, to replace the old generation, *n-people* agents are sampled stochastically to constitute the new generation. In the standard deviation mechanism there are two reference values: population average and population average plus standard deviation. Agents with *fitness* greater than, or equal to the population average are replicated once, while agents with *fitness* equal to or greater than population average plus a standard deviation are replicated twice. Finally, the average selection mechanism is similar to the mechanism of standard deviation. In this case, all agents with *fitness* equal to or greater than the population average are replicated twice. In order to keep the population size constant, in the standard deviation and average selection mechanism, we randomly eliminate or replicate agents of the new generation.

3.2 RESULTS

In the present contribution, we have defined a set of experiments that correspond to a subset of the different scenarios of resource pressure studied in the original paper. In particular, (see Table 2) we have chosen three cases of the intermediate-stress regime, one of the high-stress regime and one of the low-stress regime. The parameterization of the model corresponds to the one defined in the original work (Pereda et al., 2017b). Each experiment was run 5×10^3 generations (to be sure that the stationary was reached) and replicated 100 times.

Table 4. Experiments of selection mechanisms

Experiment	prob-resource	min-energy
Low-stress regime	0.8	0.2
Intermediate-stress regime 1	0.6	0.4
Intermediate-stress regime 2	0.5	0.5
Intermediate-stress regime 3	0.4	0.6
High-stress regime	0.2	0.8

Fig. 9 shows the average values of *correlation* and *given-energy* obtained for each scenario after 100 runs. The results do not vary significantly with respect to the ones obtained in the original work. It is only in the low-stress scenario that the new experiments show greater variability. The reason behind this change is the fact that with the new selection mechanisms the probability of changing the strategy is greater in comparison to the random tournament, where the probability of change was mainly driven by mutation. The new selection mechanisms implemented, aside from the mutation probability, in the case of equal payoffs, mix and shuffle the population strategies more intensively than the random tournament, allowing to move more in the average population strategy space at each run. In any case, the average results of *correlation* and *given-energy* are equivalent to the original ones for the three regimes identified, which means that the conclusions obtained by Pereda et al. are robust in all the identified regimes, i.e., that the three regimes are stability points of the system under consideration, since they are not affected by the different dynamics which can be imposed to the system.

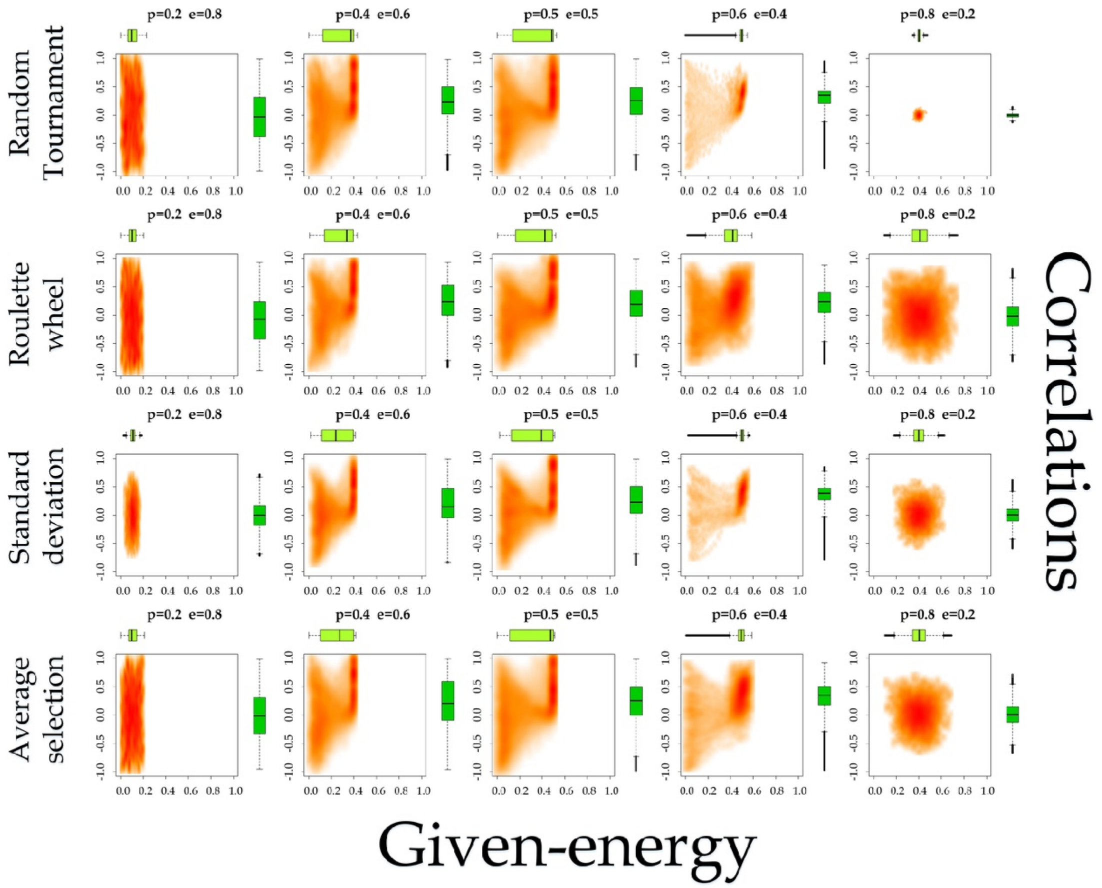

Fig. 9 This figure shows the simulation results obtained for each evolutionary or learning selection mechanism analysed, five combinations of parameters have selected for each selection mechanism. Each subfigure shows the density of the simulation results of the model in the space of the averaged strategies of the population: (i) given-energy (horizontal axis) and (ii) correlation (vertical axis) and two box-plots to summarize and compare the distributions. The parameters prob-resource (p in titles) and min-energy (e in titles) correspond in the left column to a high-stress regime, in the right column to a low-stress regime, and the three central columns to mid-stress regimes. In this smoothed colour density scatterplot, darker values (red) indicate a higher probability of the simulation to be found in the corresponding averaged population states. The outcomes obtained show that the results and conclusions of the model are robust to the mechanisms analysed.

As a consequence of all the above, the present work shows that the patterns found about the stable regimes are resilient and robust to the different types of dynamics. This suggests that even though the evolutionary dynamics of the real system may be different from the dynamics implemented, the behavioural mechanism of the population, in the absence of other processes, exhibits a strong tendency towards the patterns explained in CURP.

4. DISCUSSION

Once the robustness of the results of the CURP model has been assessed and given that after considering a comprehensive set of dynamics, the confidence on them has been strengthened, it makes sense to contextualise and analyse in depth their implications from an archaeological and anthropological point of view.

According to the model, in low-stress regimes, given the abundance of resources, no adaptive pressure pushes the dominance of a sharing strategy over the others, and the co-existence of different dynamic practices may emerge. Cooperative behaviour (a norm for food sharing) becomes predominant in the intermediate-stress regime and turns to be unstable in the high-stress regime, where no strategy seems to be stable, and many individual strategies change in an attempt to innovate for survival.

4.1 LOW-STRESS REGIME

Within the model, the low-stress regime represents a positive balance between population and resources where survival is highly probable. This sort of low-stress scenarios is often transitory and barely found in reality, since most environmental settings do not provide homogeneous resources (neither spatially nor temporally), and, as we know from biology and anthropology, most species/societies tend to increase population size with respect to the carrying capacity of that socioecological context, stabilizing by absorbing minor fluctuations due to density-independent factors that affect productivity (Hayden, 1972, 1986). It is a fact that population growth can be either brief (lasting a short time) or protracted; in any case, low-stress regimes are not the prevailing scenario in nature.

The transience of low-stress scenarios may be illustrated as the occupation of new areas or as a result of managing new resources. This conjuncture can be better exemplified as that of population processes, in which moderate population densities face new contexts. In such situations, available resources guarantee group survival until the society reaches a packed landscape (see Theler and Boszhardt (2006)), which can be attained either by demographic growth or simply by depletion of resources (which would produce “game sinks”, as defined in (Martin and Szuter, 1999; Lyman and Wolverton, 2002)). This makes the relationship with resources to change, being human populations in some cases responsible for extinction events (Faith and Surovell, 2009). Even though other causes such as forest clearance have been used to explain these extinction phenomena, it has been argued that overkill caused by humans may be the most plausible explanation (see reviews in Erlandson and Rick (2008) or Meltzer (2015)). The extinction events may be extreme, but they exemplify how human agency effects on resource availability can make it move from low-stress to intermediate-stress regime, where new mechanisms and strategies are required to survive.

In accordance with all the above, in the CURP model, low-stress scenarios correspond to contexts where no environmental or endogenous elements push towards the selection of a particular strategy since all strategies are equally likely to succeed in terms of survival. Therefore, in low-stress contexts, the agents behave selecting their strategy indistinctly from the pool of possible behaviours, or maybe just according to previous social behavioural patterns. Besides this, and because of the absence of forces driving the development of specific strategies, these contexts, although somewhat transitory, may promote some slow transitions led by random drift mechanisms (Millstein, 2002; Bentley et al., 2004). Some pieces of research have stated that random drift and stochastic processes seem to play an important role when population sizes are small (Doebeli et al., 1997; Pérez-Losada and Fort, 2011). Eventually, it has also been claimed that in areas with dense and predictable resources such as low-stress scenarios, competitive strategies may be favoured to maintain exclusive access to resources (Field, 2008).

4.2 INTERMEDIATE-STRESS REGIME

The different scenarios tagged as intermediate-stress regime correspond to contexts characterized by the discontinued appearance of resources of intermediate energy. Within the model, the agents' target is to maximize their individual fitness. In the intermediate-stress regime, the prevailing behaviour of the agents is to share resources after their individual needs for survival are met; this cooperative strategy is a mechanism to deal with the future risk of scarcity, which leads to both the maximization of individual fitness as well as to the reinforcement of collective survival. The key concept here is that food sharing and indirect reciprocity emerge as a consequence of individual fitness maximization, since retaining an additional unit of resource diminishes the probability of receiving resources from other agents.

Although there are few exceptions in which HG societies store surpluses, this mostly happens when the seasonal fluctuation of specific resources is well-known and can be expected (Testart et al., 1982; Whelan et al., 2013), such as in the case of Northwest American complex HG or Australian aboriginal groups (Ames, 1994; Lourandos, 1997). Nevertheless, most HG societies usually face unpredictability of resources through different types of mobility and sharing (Smith, 2003; Hamilton et al., 2009). In those scenarios, reciprocity is a mechanism to cope with the risk derived from environmental variability and unpredictability of resource distribution.

Regarding concepts such as stress or risk, even though they are frequently used in archaeological research, some authors claim the need for a proper definition (see a discussion in Larson et al (1996)). Several definitions of risk have been presented, in which the unpredictability over the possible outcome of a situation plays a major role (Winterhalder, 1990), while others focus on the idea of vulnerability or on surpassing a given threshold, such as that of starvation. Moreover, it can also be distinguished between those risky situations in which the possible results are known, but their probabilities are not, and situations of incomplete knowledge, in which the range of possible outcomes is unknown (Bamforth and Bleed, 2008). In both cases, unpredictability regarding resource variability forces to change the range of social decisions, sometimes with unknown or even unpredictable consequences (Rautman, 1993).

In HG contexts and in connection with risk minimization it is unavoidable to talk about the tolerated theft hypothesis (Blurton Jones, 1987), which claims that when someone is not capable of controlling a resource, she will allow access to the resource to other members of the community, as long as the cost of controlling it is much greater than the value of the resource itself (Bliege Bird and Bird, 1997; Kägi, 2001; Gurven, 2004). This hypothesis, a clear risk minimization strategy, has been considered as the origin of food transfer dynamics, as it would provide the necessary conditions for the other types of food sharing to emerge (Winterhalder, 1996).

In anthropological literature, reciprocity is used to understand how cooperation could evolve between unrelated individuals. It is also defined as the mechanism that explains how individuals make optimal decisions contingent on what others do, as the same individual acts as receptor and actor (Alvard, 2001).

In the intermediate-stress context, the heterogeneous distribution of resources happens to be a selective force that promotes the emergence and development of specific resource re-distribution mechanisms within the social domain. Reciprocal behaviour can be evolutionarily stable when individuals alternate their roles as actor and recipient so that at mid-term, investments reach all group members after some interactions (Melis and Semmann, 2010). In the case of HG, those social mechanisms for resource redistribution may be identified with the different sorts of food sharing practices, which are, in most cases, related with high-density foods and, more particularly, with meat.

These findings regarding the emergence of food sharing in intermediate-stress contexts may also assist to understand the phenomenon of the peopling of the planet. While the main part of human evolution took place in tropical areas, demographic growth, the occupation of new zones with lower or more disperse plant productivity (such as the arid areas in Africa) and the growing seasonality and heterogeneity of resources that extends towards higher latitudes, may have lead humans to adjust to major variations in food availability through social mechanisms such as food sharing (Barham and P., 2008).

For example, in the Arctic, where resources appear widely scattered, social units are highly dispersed too, so that technological innovation, as well as dynamic social organization, may have been paramount for survival (Hoffecker, 2005). Thus, it is in these mid-stress contexts where the social networks established through cooperation for survival play an essential role in all aspects of social life (Whallon, 1989). Until the 50s of the past century, most of the studies focusing on the social and economic changes faced by the Inuit communities of the North American Circumpolar regions, considered traditional food sharing bound to extinction in the face of acculturation. However, sharing as an institutionalized practice has survived and contemporary literature confirms its persistence. Even if changes appear in their material and social expression, sharing continues to be one of the organizational principles of Inuit societies and one of its most important identity traits (Lévesque et al., 2000).

Consistently with all the above, it can be asserted that the cooperative enterprise which we find in many small-scale societies is the result of a long-term evolution related to limited and fluctuating resources (Handwerker, 1983). Several ethnographic pieces of evidence point to sharing as a form of cooperation on resource consumption that allows lowering the risk of shortages (2014) (see Bhanu (2014) and references therein). During seasons of scarcity these practices are reinforced so as to maintain the wellbeing of the whole group, and especially of those members who are not capable of obtaining food through their own efforts, such as children or sick and elderly people, as it has been documented among the Pumé from Venezuela (Kramer and Greaves, 2011), the Copper Inuit (Damas, 1996) or the Yámana (Gusinde, 1937) among others. In fact, the habits of consumption can change if the situation requires it, through strategies such as rationing of daily intake (Hamilton et al., 2009).

The existence of social norms that promote sharing demonstrates the relevance of this cooperative strategy for the sustenance of the group (Witherspoon, 1975). The members that obtain resources distribute them to the rest, or put them into circulation within the group, in response to a socially established obligation (Kishigami, 2004). These prosocial interactions result not only in the provision of critical resources for group survival but are also encouraged as ethical and social obligations (Collings et al., 1998; Fortier, 2001). These interactions are maintained through the development of different social institutions, mainly normative (Horne and Cutlip, 2002; Kameda et al., 2005; Ziker, 2014), that may include different types of sanctions (Horne, 2009). Through the reinforcement of social norms, sharing becomes one of the main cultural features of HG societies. Cheater detection mechanisms, as well as control mechanisms such as punishment, parcelling, partner switching, ostracism, etc. provide solutions that allow reciprocity be evolutionarily stable (Melis and Semmann, 2010). Accordingly, food distribution is identified as an identity and solidarity symbol, and it is enormously antisocial to consume food without sharing it (Witherspoon, 1975). This solidarity affects all members of the group as the obligation reaches anyone who has more resources than those that can be immediately consumed (Fortier, 2001).

In addition, the communication channels and social networks established thanks to food sharing, provide the means around which other cooperative behaviours belonging to different life spheres may be sustained, such as the establishment of marriages (Kaplan et al., 1985; Hawkes, 1991) or political alliances among others (see a review in Patton (2005)). Moreover, it has also been argued that sharing accomplishes a signal function (Gurven et al., 2000; Briz i Godino et al., 2014) that reinforces the set of cooperative behaviours that accompany it.

4.3 HIGH-STRESS REGIME

Within the regime of high-stress, the balance between population and resources is modified. Resources become scarcer and surpluses disappear, which translates into a growing difficulty to reach the survival threshold. Very unstable behaviours characterise the mainstream trend in such cases. The agents are continuously searching for survival strategies because no strategy is sustainable or efficient enough; innovation is therefore continuously present under high-stress conditions and this scenario might be useful to understand transitional periods.

From an anthropological point of view, in contexts of high-stress such as crisis, human societies tend to apply a wide range of responses to cope with the new conditions; when the population surpasses the carrying capacity, several mechanisms rebalance the situation so that the cycle may start again.

As we asserted in the introduction, in Archaeology, it is the production domain that is mostly used to explain how societies managed these unbalances. According to this, in crisis contexts, the mechanisms implemented can be directed towards two solutions; on the one hand, towards bringing the population back down through strategies such as migration (group fission), infanticide or decline in fertility. On the other hand, other strategies can be aimed at increasing the carrying capacity (increasing the productivity through changes in extraction procedures); good examples of these strategies are specialization (the exploitation of just a narrow range of resources resources (Byers and Ugan, 2005) whose on-encounter return rates are greater than those of other resources), diversification (increasing the productivity of a given territory through an increase in the variety of the resources consumed including famine foods or other resources (see Bicho and Haws (2008)), and intensification of resource exploitation (an increase in the productive output per unit of land or labour (see a discussion in Morrison (1994))).

These economic shifts have been identified in different archaeological periods. At the end of the Upper Palaeolithic, both physical indicators of activity levels and archaeological remains indicate an intensification and diversification of resource exploitation (Villotte et al., 2010). Intensification has been extensively used to explain large socioeconomic shifts such as the transition to agriculture, which was preceded by a well-documented intensification of plant gathering (Wohlgemuth, 1996; Weiss et al., 2004b; Zeder, 2008) and animal management (Munro (2004). Besides, economic intensification has been considered a promotor of different social and organizational changes, including increasing social complexity (Johnson, 1982; Schurr and Schoeninger, 1995; Fitzhugh, 2003b).

It is interesting to note, that beyond the production sphere and the social mechanisms that can be implemented to cope with unbalances, other phenomena such as social learning, may speed up innovation rates particularly in scenarios with high-density populations (Marquet et al., 2012). Therefore, in high-stress contexts related to an increase in population, a plausible explanation for the wide exploration of strategies could be that the bigger the population, the higher the probability of knowledge and information transmission. This fact, together with a higher probability of random drift due to bigger population size, may explain the emergence of innovation in such contexts.

According to the adaptive cycle, which is one of the earliest metaphors from resilience thinkers that would latter give rise to resilience theory, extended periods of growth in which relationships change from loosely to tightly connected, are followed by release and reorganization processes (Nelson et al., 2006; Lancelotti et al., 2016). Therefore, in the context of resource crisis, organisational change is becoming an area of interest per se, as it provides a wider perspective of how human beings face resource unbalances, beyond the economic strategies mentioned.

These ideas of organisational change are perfectly coherent with the results of the CURP model since they show how under high-stress regime social agents try different alternatives, even though none of them stands out and becomes predominant. According to previous research, cooperation best emerges in contexts of stability (Nowak et al., 2004), while in high-stress regimes, instability appears together with a decrease in cooperation. Whereas the promotion of cooperation reduces intraspecific competition (Hamilton et al., 2009), high-stress contexts would promote changes in organizational strategies and the subsequent competitiveness.

When cooperative behaviours are not the primary strategy anymore, direct competition for resources may appear even among groups with different economic strategies (Bukach, 2004), leading to possible scenarios of conflict. In circumscribed contexts in which the carrying capacity has been reached, both environmental degradation and/or population stress have been commonly understood as primary sources of conflict (Theler and Boszhardt, 2006; Field, 2008).

It could be asserted that in intermediate-stress regimes societies reach a fluctuating equilibrium that enables the predominance of cooperation as a viable coordinated survival strategy. However, high-stress regimes can also emerge due to exogenous reasons that may lower resource richness with independence of the socio-ecological setting and the population size variations. Such could be the case of the Western Colonization and the Ecological Imperialism processes, in which an overexploitation of resources may have lead indigenous societies in a first instance to reinforce their cooperative strategies as a way to cope with the new situation, and in other cases to cross the boundary separating cooperative behaviour from other strategies that leave aside reciprocity. This shift from intermediate-stress to high-stress regime may enlighten the social breakdown of indigenous populations that induced the disappearance of their traditional lifestyles, forcing them to change to survive.

5. CONCLUSIONS

CURP analyses how individuals in environments with changing resource availability interact with other individuals either through cooperative (food sharing) or selfish strategies, producing as result an aggregate social behaviour. The model gives insights on how human societies may have faced changes in resource availability due to the occupation of new territories, socio-ecological changes or demographic growth among others.

We have assessed the robustness of the CURP model to some of the most popular selection and learning mechanisms. Our analysis confirms that the model leads to the same persistent regimes –low-stress, intermediate-stress and high-stress– regardless of the dynamics imposed. The particular regime reached by the population is determined by the resource pressure.

Once confirmed the robustness of the model, which strengthens our confidence in the results obtained, a detailed archaeological and anthropological contextualization of CURP results has been provided, indicating how societies may implement, increase or lower food sharing strategies when facing stress of different magnitudes. This helps to hypothesize and better understand possible past behaviours and how resource crisis were overcome in the context of hunter-gatherer societies. In particular, our results highlight the role of indirect reciprocity as a population coordination mechanism that promotes cooperation in the form of food sharing.

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5. QUANTIFYING THE RELATIONSHIP BETWEEN FOOD SHARING PRACTICES AND SOCIO-ECOLOGICAL VARIABLES IN SMALL-SCALE SOCIETIES: A CROSS-CULTURAL MULTI-METHODOLOGICAL APPROACH

Virginia Ahedo, Jorge Caro, Eugenio Bortolini, Débora Zurro, Marco Madella, José Manuel Galán

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ABSTRACT

This article presents a cross-cultural study of the relationship among the subsistence strategies, the environmental setting and the food sharing practices of 22 modern small-scale societies located in America (n=18) and Siberia (n=4). Ecological, geographical and economic variables of these societies were extracted from specialized literature and the publicly available D-PLACE database. The approach proposed comprises a variety of quantitative methods, ranging from exploratory techniques aimed at capturing relationships of any type between variables, to network theory and supervised-learning predictive modelling. Results provided by all techniques consistently show that the differences observed in food sharing practices across the sampled populations cannot be explained just by the differential distribution of ecological, geographical and economic variables. Food sharing has to be interpreted as a more complex cultural phenomenon, whose variation over time and space cannot be ascribed only to local adaptation.

INTRODUCTION

The relationship between species and their environment constitutes a recurring subject matter. Research disciplines such as Behavioural Ecology (BE) and Human Behavioural Ecology (HBE) emerged to provide scientific insights into this issue.

BE investigates how behaviour evolves in relation to ecological conditions, considering these as both the physical and social aspects of the environment (Davies et al., 2012). BE has two main lines of investigation: (i) the analysis of how measurable variation in ecological conditions predicts variability in individual behavioural strategies; and (ii) the evaluation of the fitness displayed by individuals as a consequence of their behavioural strategies, (fitness being measured through proxies such as mating success, energetic return, survival rate, or viability). This second approach led to the formation of the so-called “adaptationist stance”. The basic tenet of this line of research is that organisms living in the natural world tend to adjust their behaviour towards an optimum to maximise their fitness under given ecological conditions.

This arises from a strict interpretation of the role of environmental pressure within Darwinian natural selection, i.e., that selection, other things being equal, favours genes of individuals who are prone to behave optimally in the specific environmental conditions in which they live (Grafen, 2006). In this context, selection should favour different individual and/or social adaptive mechanisms allowing the bearers to acquire or develop locally adaptive behavioural strategies within a range of environments (Pigliucci, 2005). Examples of such an evolutionary approach can be found in the works on the development of models to explain foraging (Optimal Foraging Theory) or reproductive and demographic behaviour (Krebs and Davies, 1996).

HBE is defined as the study of human behaviour from the perspective of its adaptiveness, i.e., as the extension and application of the models developed by BE to the particular case of Anatomically Modern Humans (Nettle et al., 2013). HBE maintains that the study of human behaviour does not entail different explanatory approaches from those used for any other animal species (Mace and Jordan, 2011). HBE considers human behaviour as embedded within a given ecological context (Nettle et al., 2013), centring its investigation on production, distribution and reproduction. The first HBE papers appeared in the 1970s and focused mainly on explaining foraging patterns in hunter-gatherer populations (Smith et al., 1983). The focus on foragers was mostly due to the long-term perspective offered by such subsistence strategy, and because many researchers considered that small-scale foragers facilitated a straightforward application of Optimal Foraging Theory. In addition, this framework regarded small-scale societies (hereinafter SSSs), and in particular hunter-gatherers, as low-developed groups in which ecological laws could be more easily identified (Flannery, 1972; Descola and Pálsson, 1996). HBE has therefore extended the adaptationist BE paradigm to the study of the relationships and interactions between human populations and their environments (Smith, 2000; Winterhalder and Smith, 2000; Borgerhoff Mulder and Schacht, 2012). Nevertheless, substantial debates have arisen on whether and how far adaptationist approaches are applicable to humans (Smith, 2009), and what elements drive human cultural variability (Smith, 2011c). Its main detractors refer to human adaptationism as over-simplistic and systematically overlooking the role played by human interactions and cultural transmission mechanisms (Smith et al., 2001; Brown and Richerson, 2014).

Over the last few decades, there have been several studies aimed at the analysis of human variability in different environmental contexts (Smith and Winterhalder, 1981). More specifically, different comparative studies theoretically grounded in HBE have shown the existence of a relationship between social and ecological parameters, so that human inter-population diversity also reflects adaptation to local habitats (Nettle, 2009; Mace and Jordan, 2011). However, most HBE studies generally focus on the analysis of a specific phenomenon or a specific social attribute of a single group (foraging, distribution -cooperation and social structure-, mate choice, mating systems, reproductive decisions, parental investment, etc). The foregoing is mainly due to the considerable contribution of Anthropology to HBE, with studies generally representing the field observations of a single field researcher from a single population, usually a single site (Nettle et al., 2013).

One of the topics widely explored from the HBE perspective is that of food sharing, a universal phenomenon that can be found cross-culturally in humans, but which has also been documented in other species such as primates, where it is referred to as an “unresisted transfer of food” among unrelated adults (Jaeggi and Gurven, 2013). Studies pointing at the influence of environmental and socio-ecological variables (e.g. availability, distribution and predictability of resources) on food sharing practices are easily found in the literature (Kaplan and Gurven, 2005; Nettle, 2009).

Sharing practices background

Food sharing has traditionally been considered a characteristic feature of both human and several non-human societies, and its importance has been highlighted in studies about the evolution of cooperation and sociality, the social division of labour, the development of morality, the transition from earlier hominids to modern humans, and from hunting and gathering to agriculture (Gurven et al., 2000). In humans, sharing of resources and information is also considered a key aspect in reducing intraspecific competition and increasing population carrying capacity, per-capita growth rate and social stability (Hamilton et al., 2009). Therefore, analysing the cultural variability of this phenomenon and the role played by the different variables involved is essential for understanding human societies.

Sharing happens to be a deeply rooted and complex phenomenon, that ethnographic sources consistently describe as sequences of dynamic events (stages) resulting from highly differentiated forms of individual and group-based interactions (Enloe, 2003; Caro, 2017); interestingly, those stages are combined differently within each society (Bodenhorn, 2000; Kishigami, 2004) constituting an identity trait (Witherspoon, 1975; Grier, 2000; Lévesque et al., 2000; Benz, 2010). (Note that by stage we mean the differentiated and successive temporal, spatial and relational steps in which the activities related to sharing practices occur).

These pro-social interactions do not only influence the welfare of the group, but are also encouraged as social and ethical obligations (Kishigami, 2004) that lead to the development of diverse institutions, mainly of normative kind (Kameda et al., 2005; Horne, 2009; Ziker, 2014), upon which depends the maintenance of social networks (Fortier, 2001).

Resource and information sharing have been identified as a long-term strategy to manage risks related with the heterogeneous spatial and temporal distribution of existing resources, as well as to face the imbalances produced between resource availability and population size (Hamilton et al., 2009; Pereda et al., 2017b). In addition, factors such as economic crises and colonisation processes are known to exert notable influence on the reinforcement and intensification of sharing behaviours (Bodenhorn, 2000; Macdonald, 2000; Ziker, 2014).

Most traditional studies on food sharing among hunter-gatherers focus on the individual characteristics of a specific society (micro-scale analysis) (Malinowski, 1922; Evans-Pritchard, 1940; Mauss, 1954; Woodburn, 1998). Typically, those studies elaborate on the reasons behind its emergence and development, which are generally associated to resource abundance or to resource pressure (Rodnick and United States. Bureau Of Indian Affairs, 1938; Ewers, 1955; Damas, 1996; Harder and Wenzel, 2012; Bhanu, 2014; Pereda et al., 2017b).

With the advance of Evolutionary Biology and Ecology, sharing practices were described in terms of fitness and analysed based on their actual or perceived benefits to group physical and social survival (Gurven, 2004; Kaplan and Gurven, 2005; Hames and McCabe, 2007; Jaeggi and Gurven, 2013). Following this line of research, several models were developed to explain the origin and motivations of sharing (Gurven, 2004; Jaeggi and Gurven, 2013) and their possible link to environmental features (Bird, 1997). Particularly noteworthy is the work of Winterhalder (Winterhalder, 1986), who, through a modelling approach based on Evolutionary Ecology, showed that major gains in risk reduction by food sharing are achieved in relatively small hunter-gatherer groups, and that the circumstances in which this is possible can be precisely specified in ecological terms. Other studies have pointed to similar dynamics in other species, where food sharing has been observed to occur more commonly when food availability increases (Caraco and Brown, 1986).

Nevertheless, the progression of research on human food sharing practices has been hampered by the absence of a generalised systematic classification of them, as, despite relevant attempts to establish a typology of resource transfer practices within human societies (Polanyi et al., 1957; Bohannan, 1963; Sahlins, 1972b; Fiske, 1992; Gurven, 2004; Kishigami, 2004; Gregory and Strathern, 2015), the development of a systematic description of sharing practices in which every basic unit appears as a mutually exclusive category, with no ambiguity in the terms used, in which any type of transaction can be integrated, and applicable without significant distortions to any human socioeconomic formation, has remained incomplete (Hunt, 2000; Enloe, 2003; Widlock, 2013) until Caro's doctoral thesis (Caro, 2017). This fact has restricted research in the field to the predominant traditional and evolutionary approaches (Kitanishi, 2000; Enloe, 2003; Marlowe, 2004; Widlock, 2013).

Consequently, in overall terms, all previous research on sharing can be classified into two main categories: (i) single-case analyses with documentary nature and (ii) evolutionary modelling approaches. Remarkably, none of the works falling under these two categories deals with the systematic classification of human food sharing practices, and the vast majority of them neither implement sophisticated data analysis techniques nor perform cross-cultural comparisons to look for generalities.

Research proposal

In the last few years, there has been a growing interest in cross-cultural studies, mainly due to the creation and development of various global databases presenting cultural, linguistic and environmental data in a unified, standardised and accessible way. Initiatives such as the Human Relation Area Files (eHRAF - http://hraf.yale.edu/), D-PLACE (Database of Places, Language, Culture and Environment - https://d-place.org/ (Kirby et al., 2016)) and Seshat (Global History Databank - http://seshatdatabank.info/ (Turchin et al., 2015)), among others, are becoming key for the future of research on human, social and economic development, and promise to fill the various gaps that still make cross-cultural comparison somewhat difficult.

Accordingly, several inspiring examples of cross-cultural studies can be found in the literature, being the range of phenomena covered significantly varied: Garfield et al. (Garfield et al., 2016) focused on hunter-gatherers and report on the cross-cultural occurrence of different modes and processes of social learning in distinct cultural domains from the ethnographic record; in the work of Sorokowska et al. (Sorokowska et al., 2017), the authors focused on basic taste preferences in three populations (Polish, Tsimane' and Hadza), covering a broad difference in diet due to environmental and cultural conditions, dietary habits, food acquirement and market availability; finally, the research by Reyes-García et al. (Reyes-García et al., 2016) is also an insightful cross-cultural analysis of three subsistence-oriented societies: the Tsimane' (Amazon), the Baka (Congo Basin) and the Punan (Borneo); in it, they found that variations in individual levels of local environmental knowledge (both culturally transmitted and individually appropriated) relate to individual hunting returns and self-reported health but not to nutritional status, a paradox that is explained through the prevalence of sharing (individuals achieving higher returns to their knowledge transfer them to the rest of the population, and therefore no association between knowledge and nutritional status is found).

Inspired by the increasing number of cross-cultural studies and by the existence of numerous ethnographic examples pointing to the emergence of food sharing practices as a consequence of socio-environmental conditions, such as -among others- the cases of the Yámana hunter-fisher-gatherer society of Tierra del Fuego (Argentina-Chile), the Blackfoot (North-western USA – South-western Canada) and the Copper Inuit (Northern Canada), we decided to conduct a cross-cultural analysis on the possible effect of socio-ecological variables in the emergence of food sharing practices.

For a better understanding of the ethnographic examples that inspired this work, let us elaborate on the Yámana, the Blackfoot and the Copper Inuit cases. The Yámana society was organised in small social units based on households that showed periodical episodes of aggregation. These aggregation episodes occurred in relation to sporadic and unusually high amounts of food resources, such as the stranding of a whale or a high agglomeration of small fish. According to ethnographic sources, the Yámana displayed cooperative behaviours supported by an indirect reciprocity mechanism: whenever an exceptional food resource was discovered, this presence was signalled (through smoke signals) to other groups, bringing together people from wide expanses, so that they could share the food and exchange different types of social capital (Orquera, Luis and Piana, 1999; Santos et al., 2015; Pereda et al., 2017b). This ethnographically documented example shows how the environmental distribution of resources (the perchance presence of an extraordinary and unpredictable amount of food) can generate specific distribution practices, which are different from those developed during daily life. In addition, it highlights how the temporal variability of food resources can influence the development of specific socioeconomic practices.

In contrast to the Yámana example, the sharing practices of the Blackfoot and the Copper Inuit (both members of the sample of societies explored in this work) were influenced by resource pressure instead of resource abundance. According to (Ewers, 1955), periods of reduced food consumption due to lack of game were common among the Blackfoot and other populations of North America, which entailed changes in consumption patterns and a tendency to share equally the limited food returns. With regard to the Copper Inuit, in (Damas, 1996) Damas describes the development of a partnership system as a kind of insurance against food shortages.

Hence, in the light of all the above, we decided to conduct the present study, whose aim is to formally assess to which extent the distribution of traditional food sharing practices observed across the 22 SSSs selected can be explained by: (i) local adaptation to different environmental settings; (ii) the different set of subsistence activities developed by each society in their environmental setting; and (iii) the geographic distance between sampled populations. These possible explanations are not mutually exclusive and, more importantly, there might be other variables affecting/explaining sharing practices, (such as those related to the cultural component (Kaplan and Gurven, 2005)). However, the scope of the present work is restricted to the three aforementioned aspects.

A strong relationship between food sharing practices and the environment/subsistence activities may suggest that, to a large extent, they are the result of local adaptations to contextual conditions. If instead geographic distance drives the observed variability in sharing practices, results may suggest a mechanism of adoption of ideas from neighbouring groups, in which similarity in sharing or other cultural practices is dependent on the probability of interaction between communities (Neiman, 1995). If none of the proposed explanations is supported by the empirical distribution observed in food sharing practices, results will make it possible to envisage other processes such as cultural inheritance, or the possibility of functional convergence (i.e., that the different societies develop their sharing practices independently and on grounds of functionality).

The link between socio-cultural traits and environmental settings can be tackled in two ways: (i) through the analysis of purely environmental variables or (ii) by analysing environmental conditions in terms of their social utility (space and temporal resource availability, carrying capacity of the environment, etc.) (Lancelotti et al., 2016). We consider the latter to be the most suitable approach for our study, since the different systems of resource redistribution among humans connect the social domain of production with the individual domain of consumption. In this perspective, food-sharing practices have a prominent role in determining how fundamental resources are distributed in SSSs.

With respect to the state-of-the-art analysis conducted in the section entitled “Sharing practices background”, it is important to note that our contribution presents three main differential aspects: (1) it employs Caro’s systematic description of sharing practices (Caro, 2017), which enables to compare the food sharing sequences of different human societies, and to compute quantitative measures to assess the possible relationships between groups in terms of their mutual overlap in sharing practices; (2) it studies human food sharing behaviour from a cross-cultural perspective instead of a local one, (we look for broad patterns at continental scale through the analysis of 22 modern SSSs documented in the Americas and Eastern Siberia); (3) it implements last generation quantitative analysis techniques (exploratory statistics, networks and supervised learning predictive algorithms) to evaluate the role of environmental settings and resource availability in shaping food sharing practices.

MATERIALS

DATABASES AND DATA SOURCES

The focus of this exploratory analysis is on the Americas, a geographically self-contained area with considerable socio-ecological diversity. At the same time, the inclusion of Eastern Siberia provides a useful case-control on the role of local adaptation to Arctic areas, as well as a potential source of information on the peopling of the Americas (Reich et al., 2012; Raghavan et al., 2015; Rasmussen et al., 2015; Skoglund et al., 2015).

Having chosen the geographical area, the 22 modern SSSs studied (Fig. 10) were selected on the basis of the availability of environmental data, general economic data, and specific information on sharing practices. A database gathering all this information was created (see below the detailed description of all the variables in the database).

Fig. 10. Geographical distribution of the 22 SSSs selected. (Made with Natural Earth).

Using ethnographic information extracted from the Human Relation Area Files database (eHRAF – http://hraf.yale.edu/) and other relevant literature (see (Caro, 2017)), we constructed an inventory of the food sharing practices recorded in the 22 SSSs selected. Information related to the environmental and economic variables was extracted from Murdock's Ethnographic Atlas (Murdock, 1967) and/or Binford Hunter-Gatherer (Binford, 2001), available at the Database of Places, Language, Culture and Environment (D-PLACE – https://d-place.org/ (Kirby et al., 2016)). The relation of field and coverage dates for the different variables in each SSS can be found in Table 5; (note that according to eHRAF user guide (eHRAF User Guide), field date is the date the researcher conducted the fieldwork or archival research that produced the document, and the coverage date is the date or dates that the information in the documents pertains to -often not the same as the field date-).

Table 5. Field and coverage dates of each SSS according to the different data sources.

		Sharing practices information			Environmental and economic variables
Society (eHRAF & literature name)	**Society (D-PLACE name)**	**References**	**eHRAF Field Date**	**eHRAF Coverage Date**	**D-Place Data Field Date**
Copper Inuit	Copper Inuit	Damas 1972 (Damas, 1972), 1996 (Damas, 1996)	1962-1963	Pre-contact - late 1960s	1920 (Copper Inuit, 2016)
Blackfoot	Blackfoot	Ewers 1955 (Ewers, 1955), Nugent 1993 (Nugent, 1993)	1941-1951	ca. 1750-1952	1850 (Blackfoot, 2016)
Chipewyan	Dene	Sharp 1981 (Sharp, 1981), 1994 (Sharp, 1994), VanStone 1963 (VanStone, 1963)	1960-1975	1715-1985	1880 (Dene, 2016)
Crow	Crow	Morgan 1959 (Morgan, 1959), Frey 2014 (Frey, 2014)	1859	1859	1870 (Crow, 2016)
Guaraní	Guaraní	Reed 1995 (Reed, 1995), Reed & Beierle 1998 (Reed and Beierle, 1998)	1981-1984	1900-1980s	1900 (Guaraní, 2016)
Innu Naskapi	Naskapi	Henriksen 1973 (Henriksen, 1973),	1966-1968	1900-1973	1890 (Naskapi, 2016)

		Reid 2009 (Reid, 2009)			
Kaska	Kaska	Honigmann & Bennett 1949 (Honigmann and Bennett, 1949), Honigmann & Abate 2012 (Honigmann and Abate, 2012)	1943-1945	1940-1945	1920 (Kaska, 2016)
Mescalero Apache	Mescalero	Basehart 1970 (Basehart, 1970), Basehart & Comm. 1974 (Basehart and Indian Claims Commission, 1974)	1957-1964	1800-1890	1870 (Mescalero, 2016)
Mundurucú	Munduruku	Murphy 1960 (Murphy, 1960), Murphy & Murphy 1985 (Murphy and Murphy, 1985)	1952-1953	1952-1953	1950 (Munduruku, 2016)
Stoney	Assiniboine	Snow 1977 (Snow, 1977), Beierle 2002 (Beierle, 2002)	1969-1972	1876-1977	1870 (Assiniboine, 2016)
Warao	Warao	Heinen 1973 (Heinen, 1973), Heinen & Ruddle 1974 (Heinen and Ruddle, 1974), Heinen & Beierle 2001 (Heinen and Beierle, 2001)	1966-1973	1966-1971	1950 (Warao, 2016)

Tukano Makuna	Tucano	Arhem 1981 (Arhem, 1981), Beierle 1998 (Beierle, 1998)	1971-1973	1971-1973	1950 (Tucano, 2016)
Eastern Apache	Chiricaua	Opler 1941 (Opler, 1941), Beierle 2012 (Beierle, 2012)	1931-1937	1840-1886	1880 (Chiricahua, 2016)
Jivaro	Shuar	Karsten 1935 (Karsten, 1935), Harner 1984 (Harner, 1984), Beierle 2006 (Beierle, 2006)	1916-1929	1916-1929	1930 (Shuar, 2016)
Western Apache	Western Apache	Perry 1993 (Perry, 1993), Greenfield & Beierle 2002 (Greenfield and Beierle, 2002)	no date	nineteenth century - 1980s	1870 (Western Apache, 2016)
Ndyuka	Ndyuka	Lenoir 1997 (Lenoir, 1997), Van Wetering & Thoden van Velzen 1999 (Wetering and van Velzen, 1999)	1970-1972	1970-1972	1960 (Ndyuka, 2016)
Cubeo Tukano	Cubeo	Goldman 1963 (Goldman, 1963)	1939-1940	1939-1940	1940 (Cubeo, 2016)
Barrow Inupiat	Inupiat	Bodenhorn 2000 (Bodenhorn, 2000)	1984-2000	1970-2000	1880 (Inupiat, 2016)
Nivkh	Nivkh	Shternberg et al. 1993 (Shternberg et al., 1933), Austerlitz	1890-1910	1890-1930	1920 (Nivkh, 2016)

		2010 (Austerlitz, 2010)			
Nganasan	Nganasan	Ziker 2002 (Ziker, 2002), 2007 (Ziker, 2007), 2014 (Ziker, 2014), Adem 2012 (Adem, 2012)	1992-2014	1992-2014	1930 (Nganasan, 2016)
Chukchee	Chukchi	Zhornitskaya & Wanner 1996 (Zhornitskaya and Wanner, 1996), Ikeya 2013 (Ikeya, 2013), Krupnik 1987 (Krupnik, 1987)	2003-2006	Late 19th century-2006	1900 (Chukchi, 2016)
Evenks	Evenk	Anderson 1991 (Anderson, 1991), David et al 2010 (David et al., 2010)		Mid-20th century (1950)-2000	1890 (Evenk, 2016)

Regarding Table 5, as might be expected, the field and coverage dates for the different variables across the different SSSs considered are not always coincident. This is mainly due to the intrinsic nature of Anthropology, which renders impossible the concurrent study of all societies in the globe; therefore, cross-cultural databases gather information retrieved by different authors in different field work campaigns, which generally translates into unavoidable time lags.

The 22 SSSs selected and their environments were all documented with coverage dates ranging from ca. 1750 up to 2014. Hence, one may presume the existence of a potential bias due to the differences in the periods of time when data were collected. Nevertheless, it is important to highlight that sharing is characterised by its continuity and stability over time (Ziker, 2014), which might be explained because of its key role in the preservation of social networks (Collings et al., 1998; Fortier, 2001), a role that is enacted through the development of various social institutions –mainly normative– (Horne and Cutlip, 2002; Kameda et al., 2005; Ziker, 2014) that may include different types of sanctions (Horne, 2009). By reinforcing these social institutions, traditional sharing is consolidated as an identity trait and solidarity symbol, becoming one of the main cultural features of SSSs (Witherspoon, 1975; Grier, 2000; Lévesque et al., 2000; Benz, 2010), and thus ensuring its continuity. In addition, traditional sharing of resources and information is also bolstered by other important factors such as resource pressure and/or the processes of western colonization (Hamilton et al., 2009; Pereda et al., 2017b). Many examples in the ethnographic literature show that while these factors result in deep alterations in the field of production, traditional sharing practices are maintained and even intensified in some cases (Ewers, 1955; Damas, 1996; Bodenhorn, 2000; Lévesque et al., 2000; Godoy et al., 2005; Harder and Wenzel, 2012; Bhanu, 2014; Ziker, 2014). Particularly illustrative are the cases of the Huaorani (Franzen and Eaves, 2007) and the Nunavimmiut (Nunavik Inuit) (Parnasimautik Report, 2013); within the Huaorani community, sharing is maintained -even if they have access to a market- since it meets needs not met through market participation; similarly, the Nunavik Inuit determine an acceptable level of compensation for the exploitation of their region's minerals, as well as how this compensation will be allocated fairly among their communities, based on their tradition of sharing.

In view of all the above, it can be concluded that although traditional sharing practices may have experienced some minor changes throughout history, they tend to be maintained within SSSs, with less transformations than other cultural, social or economic traits (Macdonald, 2000). This fact renders them particularly suitable for cross-cultural studies, as the potential biases related to time lags are well overcome through their stability and continuity over time.

INFORMATION ON SHARING PRACTICES

Food sharing practices in SSSs consist of a sequence of distribution events that start from the moment a resource is obtained. The order in which the different distribution events occur, however, is a distinctive trait, and varies from one society to another, making it difficult to have a cross-cultural comparison when the sequence is considered as a whole, and/or when the order of the events is taken into account.

Therefore, following Caro's systematic description of food sharing practices (Caro, 2017), we decided to split the sharing sequence into basic stand-alone units (practices) that cannot be further broken into lower-level elements. The result is a set of 14 different basic sharing practices and their systematic description (Table 6; for more detailed information see (Caro, 2017)).

Table 6. List of the 14 basic food-sharing practices.

	Code	Practice	Explanation
1	MM	Mutualism	Earn equal shares through cooperative acquisition
2	TT	Tolerated Theft	Communal and free access to the food
3	CC	Communal Consumption	Communal consumption through the celebration of feasts, public events, etc.
4	WD	Women as Distributors	Women are in charge of distributing food
5	OD	Other Distributors	A specific individual such as the chief, shaman or an elder person distributes food

6	RM	Ranked Mutualism	Earn differentiated shares through cooperative acquisition
7	KS	Kin Selection	Give food to close family or distribution within the own household
8	GS	Group Selection	Portions given to every single household of the group
9	NS	Network Selection	Portions given to partners or extended family
10	PR	Prestige	Distribution based on gaining prestige
11	SD	Status Distribution	Food transfers to specific prestigious individuals
12	DS	Demand Sharing	Distribution based on demand
13	RA	Reciprocal Altruism	Asymmetrical distribution based on contingency
14	NN	Necessity	Allocate portions to the neediest

The next step was to identify the basic sharing practices present in the sharing sequence of each of the SSSs selected. (See Table 7. For more detailed information please refer to (Caro, 2017)).

Table 7. Basic sharing practices found in the sharing sequence of each society.

Society (eHRAF & literature name)	**Society (D-PLACE name)**	**Sharing practices**	**Sources**
Copper Inuit	Copper Inuit	KS, NS, RA, CC	Damas 1972 (Damas, 1972), 1996 (Damas, 1996)
Blackfoot	Blackfoot	GS, OD, NN, DS	Ewers 1955 (Ewers, 1955), Nugent 1993 (Nugent, 1993)
Chipewyan	Dene	GS, WD, NS, PR, RA	Sharp 1981 (Sharp, 1981), 1994 (Sharp, 1994), Van Stone 1963 (VanStone, 1963)
Crow	Crow	RM, KS, WD, TT, PR	Morgan 1959 (Morgan, 1959), Frey 2014 (Frey, 2014)
Guaraní	Guaraní	KS, RA, NS, SD	Reed 1995 (Reed, 1995), Reed & Beierle 1998 (Reed and Beierle, 1998)
Innu Naskapi	Naskapi	MM, NN, DS, CC, PR	Henriksen 1973 (Henriksen, 1973), Reid 2009 (Reid, 2009)
Kaska	Kaska	KS, WD, TT, CC	Honigmann & Bennett 1949 (Honigmann and Bennett, 1949), Honigmann & Abate 2012 (Honigmann and Abate, 2012)

Mescalero Apache	Mescalero	RM, GS, PR	Basehart 1970 (Basehart, 1970), Basehart & Comm. 1974 (Basehart and Indian Claims Commission, 1974)
Mundurucú	Munduruku	NS, WD, GS, RA	Murphy 1960 (Murphy, 1960), Murphy & Murphy 1985 (Murphy and Murphy, 1985)
Stoney	Assiniboine	KS, GS	Snow 1977 (Snow, 1977), Beierle 2002 (Beierle, 2002)
Warao	Warao	KS, SD, NS, CC, RA	Heinen 1973 (Heinen, 1973), Heinen & Ruddle 1974 (Heinen and Ruddle, 1974), Heinen & Beierle 2001 (Heinen and Beierle, 2001)
Tukano Makuna	Tucano	KS, NS, RA, GS, WD	Arhem 1981 (Arhem, 1981), Beierle 1998 (Beierle, 1998)
Eastern Apache	Chiricaua	TT, KS, NN	Opler 1941 (Opler, 1941), Beierle 2012 (Beierle, 2012)
Jivaro	Shuar	SD, OD, CC, PR	Karsten 1935 (Karsten, 1935), Beierle 2006 (Beierle, 2006)
Western Apache	Western Apache	MM, DS, NS, PR	Perry 1993 (Perry, 1993), Greenfield & Beierle 2002 (Greenfield and Beierle, 2002)
Ndyuka	Ndyuka	KS, WD, NS	Lenoir 1997 (Lenoir, 1997), Van Wetering & Thoden van Velzen 1999 (Wetering and van Velzen, 1999)
Cubeo Tukano	Cubeo	KS, WD, CC, NN	Goldman 1963 (Goldman, 1963)
Barrow Inupiat	Inupiat	RM, WD, TT, NN, CC	Bodenhorn 2000 (Bodenhorn, 2000)
Nivkh	Nivkh	MM, NN, TT	Shternberg et al. 1933 (Shternberg et al., 1933), Austerlitz 2010 (Austerlitz, 2010)
Nganasan	Nganasan	RM, KS, WD, NS, PR, RA, DS	Ziker 2002 (Ziker, 2002), 2007 (Ziker, 2007), 2014 (Ziker, 2014), Adem 2012 (Adem, 2012)
Chukchee	Chukchi	RM, OD, GS, SD, NN, KS	Zhornitskaya & Wanner 1996 (Zhornitskaya and Wanner, 1996), Ikeya 2013 (Ikeya, 2013), Krupnik 1987 (Krupnik, 1987)
Evenks	Evenk	GS, OD, NN	Anderson 1991 (Anderson, 1991), David et al. 2010 (David et al., 2010)

ENVIRONMENTAL VARIABLES

The environmental variables considered are climatic and/or ecological proxies that reflect differences between the ecological settings inhabited by the selected SSSs. They include: annual mean temperature (ºC), annual temperature variance (ºC), temperature constancy, temperature contingency, annual mean precipitation (mm), annual precipitation variance, precipitation constancy, precipitation contingency, distance to the coast (km), elevation (masl) and slope (degrees).

Environmental phenomena expressed by the above climatic/ecological proxies can range from predictable to unpredictable. A phenomenon is completely predictable when it is consistently repeated every year, while it is unpredictable when all states are equally likely in all seasons (see S1 Supporting Information in (Kirby et al., 2016) and (Colwell, 1974)). Predictability has two separable components: constancy and contingency. Maximum predictability can be attained as a consequence of either complete constancy, complete contingency or a combination of the two, with respect to time. Complete constancy implies that the phenomenon is the same for all seasons in all years, whereas complete contingency means that the state of the feature is different for each season, but the pattern is the same for all years. Based on this, instead of considering these three variables for our analyses, we worked with constancy and contingency, as predictability can be obtained from the two.

ECONOMIC VARIABLES

The selected economic variables are those related to resource richness and resource necessity (in relation to population levels), as well as those related to resource management. More specifically: monthly mean net primary production (measured in grams of carbon uptake per square meter of land per month (gC m-2 month-1)), annual net primary production variance, net primary production constancy, net primary production contingency, population size, and the relative percentage of dependence on different subsistence strategies (hunting, gathering, animal husbandry, fishing, and agriculture).

Population size was considered within the economic variables, since in conjunction with net primary production, it is a good indicator of resource pressure.

For further details on the meaning of each one of these variables and their ranges please refer to S1 Appendix.

By way of summary, Table 8 presents the relation of all the variables involved in the present work and the categories to which they belong.

Table 8. Summary of all the variables considered in this study.

Basic sharing practices	Environmental variables	Economic variables
• Mutualism • Tolerated Theft • Communal Consumption	• Annual mean temperature (C) • Annual temperature variance (C)	• Monthly mean net primary production • Annual net primary production variance

• Women as Distributors • Other Distributors • Ranked Mutualism • Kin Selection • Group Selection • Network Selection • Prestige • Status Distribution • Demand Sharing • Reciprocal Altruism • Necessity	• Temperature constancy • Temperature contingency • Annual mean precipitation (mm) • Annual precipitation variance • Precipitation constancy • Precipitation contingency • Distance to the coast (km) • Elevation (masl) • Slope (degrees)	• Net primary production constancy • Net primary production contingency • Population size • Relative percentage of dependence on: • Hunting • Gathering • Animal Husbandry • Fishing • Agriculture

Finally, last but not least, pairwise geographic distance was used as a proxy for the effect that interaction between populations may have on the adoption of sharing practices. This proxy is based on the assumption that populations that are closer in space may exhibit a higher degree of similarity of both genetic as well as non-adaptive cultural traits, which could imply that SSSs geographically closer may have more similar sharing practices (Wright, 1943; Rousset, 1997; Shennan et al., 2015).

METHODS: DATA ANALYSIS

The set of analyses applied to the dataset described above, and the transformations needed to conduct them, can be summarised as follows:

1. **Exploratory analysis** of the possible relationships between each socio-ecological variable (except for geographic distance) and each basic sharing practice, across the selected SSSs. For that purpose, each socio-ecological variable was split into two groups according to the presence (1) / absence (0) –binary codification– of each of the 14 basic sharing practices, across the 22 SSSs selected. Then, the two groups were compared to ascertain if statistically significant differences exist between them. Different unpaired statistical tests were used for the different cases depending on their particularities: *t*-test, Wilcoxon test, Fligner-Policello test and/or Brunner Munzel test, (further details below).
2. **Sharing similarity network** to verify whether geographically closer societies exhibit more similar sharing practices. In this network, the 22 SSSs were set as nodes, being two nodes linked by an edge if they have in common a specific basic sharing practice. The network was represented on a map of the world in accordance with its geographical location.
3. **Formalization of dissimilarity in food sharing practices** through pairwise Hamming distance. In point 1, the analyses were restricted to evaluating the possible impact of each socio-ecological variable on the presence/absence of each basic sharing practice across the 22 SSSs. However, from point 3 on, the aim is to determine whether larger pairwise differences in the values exhibited by each SSS for the different socio-ecological variables, are linked to greater dissimilarity in sharing practices (greater Hamming distance).

Sharing Hamming distances were calculated pairwise from each of the 22 SSSs to all the rest, considering the whole sequence of food sharing practices –codified as a binary vector with 14 positions, one for each basic sharing practice. The Hamming distances obtained are quantitative values expressing how distant each pair of SSSs is in terms of sharing.

4. **Transformation of the explanatory variables** into pairwise difference variables, to be able to attain the objective described in point 3. For that purpose, we computed the difference between the values exhibited by every pair of societies for each socio-ecological variable. Pairwise geographic distance was computed as great-circle distance, i.e., the shortest distance between two points on the surface of a sphere, measured along the surface of the sphere.
5. **Exploratory analysis** by means of the Maximal Information Coefficient (MIC), Distance Correlation (dCor) and the Heller-Heller-Gorfine (HHG) measure, to check for the existence of relationships of any type between dissimilarity in sharing practices (Hamming distance) and the pairwise differences (between SSSs) of the socio-ecological variables.
6. **Implementation of supervised learning regression algorithms** to try to predict the dissimilarity in food sharing practices (Hamming distance values) taking as regressors the pairwise differences of the socio-ecological variables. The selected algorithms were Support Vector Machines (SVM) with radial kernel and ensemble methods: random forest, boosting and rotation forest.

1. EXPLORATORY ANALYSIS

It was conducted to try to identify all possible relationships between each one of the socio-ecological variables and the presence/absence of each one of the basic sharing practices, taking one socio-ecological variable and one basic sharing practice at a time. In this first analysis, the socio-ecological variables remained unchanged, i.e., we worked with the original values recorded for each variable in each SSS, (we did not take pairwise differences in values yet).

Based on the above, geographic distance was not evaluated at this stage, since it is the pairwise geographic distance that is relevant for our study, not the distances to a common origin.

Identifying the existence of any relationships between an independent categorical variable (the presence/absence of a basic sharing practice across the 22 SSSs) and an independent continuous variable (the socio-ecological variables), requires a two-sample statistical test such as the independent *t*-test (Berkman and Reise, 2012) for two samples. In our analysis, different unpaired two-sample statistical tests were used depending on the details of each case. The rationale behind all these tests, however, is quite similar: first, each socio-ecological variable is split into two groups: the one that presents the basic sharing practice under consideration and the group lacking that feature. Then, the most suitable statistic for each case is calculated, to determine if the means of the two groups are significantly different from each other (at a 0.05 significance level). The independent *t*-test is only suitable when normality and homogeneity of variance can be assumed (Delaney and Vargha, 2002). For the cases violating one or both assumptions, other tests are needed. If it is the normality assumption that is violated, the most commonly used test is the Wilcoxon-Mann-Whitney test, whose power, according to some authors, appears to be asymptotically superior to that of the *t*-test for real high quality data (Fay and Proschan, 2010). If both assumptions are violated, especially recommended are the Fligner-Policello test and the Brunner and Munzel test (Delaney and Vargha, 2002), the latter being generally better according to Fagerland MW et al. (Fagerland and Sandvik, 2009). Other authors argue that the Wilcoxon-Mann-Whitney test can be also used when both assumptions are violated, since the Fligner-Policello test and the Wilcoxon-Mann-Whitney test have been found to have roughly similar power (Feltovich, 2003).

In this exploratory phase, a total of 294 tests were run. In order to overcome the multiple testing problem, we implemented different multiple comparison corrections: two conservative approaches (Bonferroni and Šidàk (Abdi, 2007)) and a set of more flexible corrections, namely Holm, Hochberg, Hommel, Benjamini & Hochberg, and Benjamini & Yekutieli (Chen et al., 2017).

2. CONSTRUCTION OF A CULTURAL SIMILARITY NETWORK

To visualise the interrelations between societies, we built a network by setting the 22 SSSs as nodes, and where two nodes are linked by an edge if they have in common a basic sharing practice. Then, to get rid of multiple links, the network was transformed into a weighted network, where the weight of each edge represents the number of links (basic sharing practices) that the two societies have in common. The higher the weight, the greater the similarity between the sharing practices of these two societies.

3. FORMALIZATION OF DISSIMILARITY IN FOOD SHARING PRACTICES

Food sharing practices are a complex phenomenon. Each SSS has its characteristic sharing behaviour, which consists of a sequence of distribution events in which the order of appearance of the basic sharing practices is distinctive, constituting a group identity trait (Benz, 2010; Caro, 2017). (Recall that by stage we understand the differentiated and successive temporal, spatial and relational steps in which the activities associated with each basic sharing practice occur; and by order of appearance, the position in which every basic sharing practice appears within the sequence (Caro, 2017)).

At this point, a shift in focus was needed to consider all the basic sharing practices constituting a sequence together; hence, each SSS was assigned a vector with as many positions as basic sharing practices –14–, where the presence/absence of each one of them was codified in binary terms, regardless of the order of appearance. With this codification, it seemed reasonable to quantify dissimilarity in food sharing practices through Hamming distance, which, for two vectors of equal length, corresponds to the total number of positions exhibiting different values (Hamming, 1950).

The details of the binary codification of sharing practices can be found in S1 Table.

4. TRANSFORMATION OF THE EXPLANATORY VARIABLES

After the initial exploratory analysis (where all the socio-ecological variables remained unchanged), the subsequent analyses required transformations to have a coherent framework where all variables could be treated equally. The transformations required consisted in:

A) Formalizing the difference in sharing practices between societies in terms of pairwise Hamming distance -see point 3-. (This resulted in 231 values after removing the diagonal and the symmetrical values of the 22x22 dissimilarity matrix).

B) The calculation of pairwise geographic distances (great-circle distance).

C) Calculating pairwise value differences between societies for the rest of socio-ecological variables (again, 231 values were obtained for each variable after removing the diagonal and the symmetrical values). This is a key point, because it implies that except for geographic distance (where the original value was considered), the rest of the explanatory variables were analysed in terms of the difference in their values (i.e., how does the pairwise difference in value of the socio-ecological variables relate to the pairwise dissimilarity in sharing practices?).

5. EXPLORATORY ANALYSIS BY MEANS OF MIC, DCOR AND HHG

Having transformed all variables, three exploratory statistical tools (namely MIC (Reshef et al., 2011), dCor (Székely and Rizzo, 2009; Simon and Tibshirani, 2014) and HHG (Heller et al., 2013)) were used; these tools were developed to identify a wide range of associations between variables, both functional and not. Although the mathematics behind each tool are significantly different, both MIC and dCor measure the intensity of a relationship of any type, while HHG gives the probability that the relationship truly exists by means of four different *p*-values obtained for four different statistics.

MIC is a recent metric designed to capture the strength of a wide range of associations between variables. However, some authors (Simon and Tibshirani, 2014; Gorfine et al., 2015) suggest that this statistic may have shortcomings with respect to the properties of equitability and generality, as well as in terms of statistical power for samples of limited size. Therefore, we considered the concurrent use of other measures such as distance correlation (dCor) and HHG to overcome these shortcomings. The results of the three metrics complement each other and give a wider insight into the possible relationships between items. MIC and dCor measure the strength of the association between variables and HHG provides four different *p*-values: *pval.hhg.sc, pval.hhg.sl, pval.hhg.mc and pval.hhg.ml*, corresponding respectively to: 1) the sum of Pearson chi-squared statistics from the 2x2 contingency tables considered (sum.chisq); 2) the sum of likelihood ratio (*G* statistic) values from the 2x2 tables (sum.lr); 3) the maximum Pearson chi-squared statistic from any of the 2x2 tables (max.chisq), and the maximum *G* statistic from any of the 2x2 tables (max.lr) (Heller et al., 2013); (for the sake of simplicity we have used the nomenclature from the HHG package in R (https://CRAN.R-project.org/package=HHG)).

Regarding the calculation of HHG, we selected Euclidean distance for its computation, as it allows for a straightforward interpretation in the present context of application.

As 22 socio-ecological variables were considered (23 with the Hamming distance in sharing practices itself), 23 comparisons were made in this phase. Therefore, it was necessary to implement some multiple comparison correction procedures, namely Bonferroni, Holm and Hochberg (Chen et al., 2017).

6. IMPLEMENTATION OF SUPERVISED LEARNING REGRESSION ALGORITHMS

Up to this point, all the environmental and socio-ecological variables have been considered separately (one at a time); hence, we decided to apply non-linear regression algorithms (Hastie et al., 2009; Fernández-Delgado et al., 2014) to our dataset of transformed variables (pairwise differences), to check if when taken together, these variables present an explanatory power with respect to the sharing Hamming distance that they do not have when taken separately. The idea behind creating a predictive model is that it may exist a complex pattern simultaneously involving several variables that might explain the output.

In the field of data mining, there is a general consensus that ensemble methods are suitable techniques for dealing with the most difficult problems (Kuncheva, 2014). The main idea behind the ensemble methodology is to aggregate multiple weighted models in order to obtain a combined model that outperforms every single model in it (Ren et al., 2016). In addition, the family of algorithms based on Support Vector Machines (SVMs) has proved to give very good results both for regression and classification (Basak et al., 2007; Loterman et al., 2012; Fernández-Delgado et al., 2014). Therefore, we used both approaches.

An accurate predictive model needs to have a good bias-variance trade-off, which refers to the necessity of a middle-ground solution between a very general model that fails to include important details, therefore lacking accuracy (high bias), and an overfitted model which fails to generalize on new data (high variance). Ensembles are good at finding that compromise since each model in them can be somewhat overfitted, taking under consideration the singular details of its particular training data, but this effect is counteracted by averaging the outputs of all models in the ensemble. According to Fernández et al. (2014), random forest is the ensemble method most likely to obtain the best results in different scenarios. Nevertheless, the most suitable model for each case study depends directly on the details of the case, as there is no specific model which outperforms all the others in all cases cases (Wolpert, 1996). Consequently, in this work we implemented –together with random forest– other three high-performance algorithms: two ensembles (boosting (James et al., 2013) and rotation forest (Rodriguez et al., 2006; Pardo et al., 2013)) and SVM with radial kernel.

Eventually, an Analysis of Variance (ANOVA) test was conducted, to compare the accuracy of the four regression algorithms with that of the prediction of the mean (predicting the average value in all cases), and to see if the differences were statistically significant.

RESULTS

EXPLORATORY ANALYSIS

Different two-sample statistical tests were applied to the raw values of the socio-ecological variables depending on the particularities of each case (*t*-test, Wilcoxon-Mann-Whitney, Fligner-Policello and Brunner and Munzel).

The results of the 294 tests conducted in this phase can be found in S2 Table.

The details of the multiple comparison corrections can be found in Supporting Information S2 Appendix, where first the value obtained with the two conservative approaches is presented (Bonferroni and Šidàk), and then, Table B collects the *p*-values corrected according to more flexible approaches (Holm, Hochberg, Hommel, Benjamini & Hochberg, Benjamini & Yekutieli).

Even though the aim of this analysis was to detect the possible relationships between the presence/absence of each basic sharing practice (codified in binary terms) and each of the environmental and economic variables considered, for a significance level of 0.05, no significant relationships were found except for the percentage of dependence on animal husbandry and status distribution. In this case, the *p*-value obtained with the Brunner and Munzel test is so low that in accordance with all the multiple comparison corrections implemented, the null hypothesis of equality of means between the two groups –no effect of the socio-ecological variable– has to be rejected.

Because a significant relationship between the percentage of dependence on animal husbandry and status distribution is suggested by only one test (Brunner and Munzel) out of the three tests run on this case (Fligner-Policello, Brunner and Munzel and Wilcoxon-Mann-Whitney), it would be misleading to consider this result as a strong evidence of relationship. On the contrary, it suggests that a relationship may exist between these two variables, although further research on the subject would be needed to check if the relationship continues to be significant when more SSSs are considered.

CULTURAL SIMILARITY NETWORK

The output of this approach is a food sharing similarity network. After positioning the nodes (SSSs) according to their geographic location in terms of latitude and longitude, a qualitative assessment of the visualization obtained was performed. The main conclusion drawn is that simple geographic distance appears not to be related to dissimilarity in sharing practices, as societies from South America are more heavily linked (present links with greater weight) with societies in Siberia and North America than with societies that are closer to them in space.

Fig. 11. Sharing similarity network. (Made with Gephi GeoLayout and Map of Countries plugins. The maps from Map of Countries plugin were provided by thematicmapping.org).

EXPLORATORY ANALYSIS BY MEANS OF MIC, DCOR AND HHG

MIC, dCor and HHG are statistical tools conceived to capture a wide range of associations between variables. MIC and dCor measure the intensity of the association while HHG gives four *p*-values on the probability that the relationship truly exists in reality.

Table 9 presents the values of MIC, dCor and HHG *p*-values obtained for the possible relationships between dissimilarity in sharing practices (Hamming distance) and each one of the transformed socio-ecological variables (pairwise differences between their values).

Since there are four *p*-values (HHG has four different *p*-value calculation procedures), four tables with the corrected the *p*-values according to Bonferroni, Holm and Hochberg multiple comparison corrections were obtained -one table for each- (see Supporting Information, Tables C, D, E and F in S3 Appendix).

At a 0.05 level of significance, no significant relationships were found between dissimilarity in sharing practices and any of the pairwise differences in value of the socio-economic variables considered. Thereupon, the hypothesis that the more different the socio-ecological variables of two SSSs, the more dissimilar their sharing practices, is not underpinned by the statistical evidence provided by MIC, dCor and HHG.

Table 9. Values of MIC, dCor and the four p-values provided by HHG -without any multiple comparison correction-.

		Food sharing Hamming distance					
		MIC	dCor	pval.hhg.sc	pval.hhg.sl	pval.hhg.mc	pval.hhg.ml
1	Geographic Distances	0.1748	0.0834	0.9650	0.9530	0.8042	0.9700
2	Annual Mean Temperature Difference	0.2285	0.1756	0.2288	0.2707	0.5954	0.8142
3	Annual Temperature Variance Difference	0.2566	0.1374	0.3616	0.3816	0.2178	0.4316
4	Temperature Constancy Difference	0.1939	0.1612	0.0809	0.0639	0.8012	0.6204
5	Temperature Contingency Difference	0.2311	0.1811	0.0889	0.0789	0.0729	0.1528
6	Annual Mean Precipitation Difference	0.2028	0.1679	0.2567	0.2757	0.7073	0.8751
7	Annual Precipitation Variance Difference	0.1930	0.1345	0.2138	0.2248	0.1838	0.3357
8	Precipitation Constancy Difference	0.1752	0.0890	0.5534	0.5724	0.5145	0.5135

9	Precipitation Contingency Difference	0.1924	0.1483	0.2058	0.2018	0.6793	0.4915
10	Distance to Coast Difference	0.1974	0.1138	0.5065	0.5085	0.8022	0.7932
11	Elevation Difference	0.2088	0.1159	0.1079	0.0959	0.1259	0.4955
12	Slope Difference	0.1974	0.1187	0.2138	0.2398	0.4396	0.6783
13	Hunting Difference	0.1356	0.0979	0.4016	0.4046	0.1269	0.1918
14	Gathering Difference	0.1471	0.1009	0.3207	0.3417	0.5754	0.8252
15	Animal Husbandry Difference	0.0622	0.1764	0.4246	0.4496	0.5674	0.5784
16	Fishing Difference	0.1382	0.1160	0.8412	0.8641	0.7942	0.9091
17	Agriculture Difference	0.1352	0.1769	0.0839	0.0659	0.1958	0.0310
18	Monthly Mean Net Primary Production Difference	0.1911	0.1808	0.4176	0.4156	0.9600	0.9191
19	Annual Net Primary Production Variance Difference	0.1790	0.1390	0.2038	0.2068	0.3057	0.4535
20	Net Primary Production Constancy Difference	0.1985	0.1643	0.4406	0.4466	0.6603	0.3357
21	Net Primary Production Contingency Difference	0.1946	0.0885	0.4745	0.4785	0.5564	0.0719
22	Population Size Difference	0.1562	0.1012	0.6723	0.6723	0.2498	0.4745

23	Food sharing Hamming Distance	0.9924	1	0.0010	0.0010	0.0010	0.0010

IMPLEMENTATION OF SUPERVISED LEARNING REGRESSION ALGORITHMS

At this point, we implemented 4 different high-performance regression algorithms: random forest, boosting, rotation forest and SVM with radial kernel. Then, with an ANOVA test, we compared the results of each of them to the prediction of the mean (predicting the average value in all cases).

The results analysed with the ANOVA test were obtained through ten-fold nested cross-validation (Anderssen et al., 2006; Varma and Simon, 2006) (further details on the results obtained for each fold in S3 Table). The ANOVA test (see results in Table 10) showed that the null hypothesis of equal means across the five algorithms cannot be rejected for a common level of significance (0.05). This means that no pattern relating the output with the explanatory variables was detected, as top prediction algorithms trained on the data were indeed unable to reach higher accuracy than that of the prediction of the mean. Therefore, our proposition that all the regressors (the socio-ecological variables in pairwise difference terms) taken together, could have an explanatory power with respect to the sharing distance that they do not have separately, is not supported by empirical evidence; for a common level of significance (0.05), we cannot reject that the differences may be due to randomness.

Table 10. ANOVA table.

	Df	**Sum Sq**	**Mean Sq**	**F value**	**Pr(>F)**
Model	4	1.82	0.4557	0.37	0.829
Residuals	45	55.46	1.2325		

ANOVA test conducted on the MSE obtained by means of 10-fold nested-cross-validation for random forest, boosting, rotation forest, SVM with radial kernel and the prediction of the mean. The null hypothesis of equality of means across all of them cannot be rejected for alpha = 0.05.

This result validates our previous findings and confirms the lack of relationships between the observed distribution of sharing practices and the environmental and socio-ecological variables considered.

DISCUSSION

The results from our analyses point to a generalised lack of statistically significant relationships between food sharing practices and the considered environmental and socio-ecological variables, at the chosen scale of analysis and across all methodologies implemented, i.e.: (1) in terms of direct relationship between each basic sharing practice and each explanatory variable; (2) regarding the network approach, as the sharing similarity network does not support the hypothesis that sharing practices of geographically closer populations may be more similar; (3) in terms of the possible relationships between the pairwise differences in the values of the explanatory variables and the pairwise Hamming distances between sharing practices; and (4) when implementing supervised learning regression algorithms to look for complex patterns simultaneously involving several variables, since no pattern between the regressors (in pairwise difference terms) and the distance in sharing practices was found.

A positive result, however, was obtained with approach (1) for the possible relationship between the percentage of dependence on animal husbandry of a SSS and the presence of sharing practices dominated by status distribution. Since only one test out of three pointed to a significant relationship, this result should be interpreted as a suggestion of relationship, not as a strong evidence of it.

In the literature, several authors pointed to a connection between the beginning of pastoralism (with the important surplus generated by cattle and/or sheep/goats) and the emergence of social stratification linked to status (Guy, 1987). This result is in accordance with other modelling approaches (Smith and Choi, 2007) which suggest that institutionalized social inequality in non-coercive circumstances might arise due to a limited number of asymmetries in a system, such as the control over productive resources or of socially significant information. The outcome of these asymmetries would be the concentration of wealth (or power) in a segment(s) of the social group. In addition, the models in (Smith and Choi, 2007) suggest that such asymmetries can be self-reinforcing and therefore, quite stable over time. An ethnographic example illustrating this phenomenon can be found in the Kalahari desert, where access to water-storing melons and domestic animals led to wealth inequality and increased polygyny (Cashdan, 1980), which is linked to stratification.

Hence, (aside from the suggestion of relationship between animal husbandry and status distribution), based on the results of our analyses we cannot reject the null hypothesis of independence between the selected socio-ecological variables and food sharing practices at the current scale of analysis. There are several reasons that may account for this absence of non-random relationships and which may be grouped under two main categories: (a) missing proxies and (b) additional possibilities.

Regarding missing proxies, it should be emphasized that food sharing practices are a multifaceted phenomenon resulting from the interaction of numerous intertwined mechanisms. The present contribution, because of the HBE approach selected, focused on environmental and socio-ecological variables, leaving aside other factors that may be explicative. However, in the light of the results obtained (no statistically significant relationships found), one may expect that it is the unconsidered proxies that might explain the cross-cultural differences in food sharing practices.

Among the set of possible missing proxies, it could be of interest to consider: (i) the use of a different scale of analysis –particularly a lower one; (ii) the inclusion of the stages and/or the order in which the basic food sharing practices are performed within the sharing sequence; and (iii) the examination of the processes of cultural transmission and cultural diffusion, as well as the possible mismatch between the context where practice emerged and the context where it is implemented.

(i) The scale of analysis

The selection of an adequate scale of analysis is critical for the emergence of robust patterns of change in socio-ecological variables, which can then be compared with variability in sharing practices. It is necessary that the scale of analysis coherently articulates with the hypothesis to test, and that it is compatible with the methodology selected. This work was conducted at a macro-scale, i.e., with a sample of SSSs scattered at continental level. Nonetheless, the absence of relationships at this scale of analysis (cross-continental) does not imply that such relationships do not exist at other scales. In fact, Ember et al. showed in (Ember et al., 2018) that at a worldwide scale, patterns in food sharing can be observed. More precisely, they found that societies subject to more resource stress share more frequently. At lower scales of analysis, such as subcontinental, regional or with a smaller-sized sample of societies, patterns may also be found. A good example of it is the work conducted by Patton (Patton, 2005) between households of Achuar, Quichua and Zapara speakers in Conambo –an indigenous community of horticultural foragers in the Ecuadorian Amazon. In it, it is stated that transfers of meat in Conambo are best explained by multiple adaptive strategies, many of which are better understood with reference to the political context. Conambo is a game-rich environment (resource richness), allowing for small meat-sharing networks and direct accounting and policing of transfers. As a result, hunters in Conambo exercise control over meat transfers, can more easily practice conditional giving, and target meat transfers to reciprocating households, kin and political allies.

(ii) The inclusion of the stages constituting the food sharing sequence

Considering the stages in which the whole sharing sequence can be divided is to some extent related to the scale of analysis too. These stages denote the order in which individuals share the obtained resources across the different spheres within the kinship or communal network (Caro, 2017). Thus, food sharing stages constitute at the same time scales of analysis such as close vs. extended kinship (Dyble et al., 2016).

Although, as discussed earlier, many of the basic sharing practices constituting a sharing sequence are observed cross-culturally, the order in which those basic practices are performed is specific of each group and can be considered an identity trait (Benz, 2010; Caro, 2017). Therefore, the observation units chosen may have had a limiting or biasing effect on the analyses conducted. We focused on the presence/absence of the 14 basic sharing practices (Caro, 2017) in the whole sharing sequence of each SSS, regardless of the order of appearance. However, it could be argued that the main feature to consider should be the stage at which each practice takes place (what would require comparing stages), or that it is the whole sequence with its intrinsic order that should be considered, (which would imply whole-sequence comparisons).

(iii) Cultural diffusion, cultural transmission and the mismatch argument

Human cultural variability often depends on non-environmental or non-adaptive mechanisms shaping social behaviour. Hence, for a more comprehensive understanding of cultural phenomena –and specifically of sharing practices–, the competing effects of a great variety of processes of cultural transmission and cumulative cultural change should be considered.

Since the emergence of Dual Inheritance Theory and the study of gene-culture coevolutionary processes (Cavalli-Sforza and Feldman, 1981; Boyd and Richerson, 1985), relevant literature defines cultural transmission as the process by which information is copied, imitated and learnt among conspecifics of the same generation, and passed on to the following generations. Mechanisms underpinning the distribution observed in cultural and behavioural traits may be for example related to the movement of people (i.e. a *demic diffusion*, by which material and immaterial concepts move following the migration of humans carrying them) and, in some cases, to gradual or abrupt population replacement. Alternatively, the spread of ideas and the exchange of information between neighbouring individuals and groups may take place without necessarily entailing migration events or population replacement (i.e. *cultural diffusion*). The above-mentioned scenarios are not mutually exclusive. Both have a relative impact on the total variability recorded in empirical observations that may be formally ascertained (Pinhasi and von Cramon-Taubadel, 2009; Fort, 2012, 2015; Creanza et al., 2015; Bortolini et al., 2017). It should be stressed that a scenario based on cultural diffusion implies a longer temporal scale in which cultural information is gradually passed on from one group to the next until a cultural or social barrier is encountered. In addition, spatially closer populations interact more often and more intensely than populations located further apart (Wright, 1943; Rousset, 1997; Ramachandran et al., 2005; Shennan et al., 2015). The iteration of this process makes geographic distance a good proxy of cultural (or biologic) dissimilarity and generates geographic clines.

Another plausible explanation for the absence of relationships found –which is also related to demic diffusion processes– is the possible mismatch (Mace and Jordan, 2011) between the context where a cultural trait emerged/developed and the context where it was observed. This may be due not only to population movements, but also to changes in the environment (either for natural or anthropic reasons). Remarkably, mismatch arguments have been claimed to be larger in the case of human societies when compared to other species due to the specific role played by technology (Laland and Brown, 2006).

To illustrate all these ideas in the context of sharing, we can think of a society whose sharing practices were developed in a specific environmental setting and which were later exchanged due to proximity to other social groups, or which eventually reached areas far from their geographic origin through migration. In the ethnographic record, both contacts with other groups and/or migratory events are documented for some of the 22 SSSs studied in this work, such as –among others– the Crow, the Blackfoot and the Stoney (all located in the present USA). The Crow are documented to have performed westward migratory processes early in the eighteenth century; as a consequence, they came into continuous contact with other social groups –both for warfare and/or trade–, which possibly resulted in the exchange of different cultural and socioeconomic traits (Voget, 1980, 2001). Migration is also recorded among the Blackfoot. According to (Grinnell, 1892), the Blackfoot tribes were not created in the land which they inhabited at the end of the nineteenth century; probably within 200 years from Grinnell's publication, the Blackfoot were not plains people, but lived far to the northeast, possibly near or north of Lesser Slave lake. Something similar is reported for the Stoney; in (Andersen, 1970) we find that the Stoney may have been in the foothills west of Edmonton by about 1650 and that a mid-17th century entry into the area would roughly coincide with the westward push of Cree and Stoney from around Lake Winnipeg, which presumably began about 1670 and for which two different migration routes into the Rocky Mountains are suggested; later, pressures from adjacent groups may have helped them move further west.

In view of all the above, the absence of significant relationships between sharing practices and environmental/ecological variables hints at a marginal role played by adaptation to localised conditions and subsistence strategies devised to face different selective pressures. At the same time, the lack of correlation between dissimilarity in sharing practices and pairwise geographic distance suggests that interaction between groups, horizontal exchange of information, and cultural diffusion may not be the key mechanisms underlying the distribution of sharing practices across the study area; a representative example supporting this assertion is that of the Cubeo and the Tukano (both in the present Colombia), whose sharing practices are significantly different despite being extremely close in space (see Fig. 10 and Table 7). Migration could then have had a critical role in shaping the observable distribution of food sharing practices, as it is suggested by the strong similarity found between some South American and North-western American/Siberian societies (Fig. 11); particularly noteworthy is the example of the Chipewyan (Canada) and the Mundurucú (Brazil), whose sharing practices are almost identical except for the fact that distribution based on prestige (PR) is only performed among the Chipewyan (Table 7). Thereupon, human groups may have developed sharing practices in a specific context and may have moved throughout the study area too quickly for a geographic gradient to form (Wright, 1943; Shennan et al., 2015).

Beyond their emergence in specific socio-ecological conditions, food-sharing practices display a clear component of inherited behavioural dynamics connected to social organization. Thus, a worthwhile future research line would consider the study of common ancestry between pairs of sampled populations, to quantify the relative effect of demic diffusion as opposed to cultural diffusion and mere functional convergence (i.e. independent development of cultural traits or behaviours without inheritance or exchange of information) (Crema et al., 2014).

Leaving aside the possible role played by missing proxies and unknown variables, the obtained results might be interpreted in the light of two additional arguments: (1) niche construction theory and (2) Galton's problem.

Niche construction theory

Niche construction theory (NCT) is a fledgling branch of evolutionary biology that places emphasis on the capacity of organisms to modify natural selection in their environment and thereby act as co-directors of their own, and other species' evolution (Laland and O'Brien, 2010).

Human niche construction may be uniquely potent, being the capacity for technology and culture a critical factor underlying such potency.

Mathematical models have shown that niche construction due to human cultural processes can be as powerful as niche construction due to biological evolution (Laland et al., 2001), and, what is more, that because cultural processes typically operate faster than natural selection, cultural niche construction probably has more profound consequences than gene-based niche construction (Laland and O'Brien, 2010). There is now little doubt that human cultural niche construction has co-directed human evolution (Laland et al., 2010), and that cultural niche construction can modify the selection of human genes and drive evolutionary events (Laland et al., 2001; Ihara and W. Feldman, 2004; Creanza and Feldman, 2014). Therefore, the relationship with the environment is bidirectional and human activities do not only modify the environment, but also influence biological selection processes as a consequence of their cultural behaviour. There may be instances of local cultural adaptations, which produce a threefold feedback over time on cultural variability, ecological variables, and the genetic pool of those specific populations generating cultural niches (John Odling-Smee et al., 2003). Hence, human cultural niche construction may also have its part in the explanation of the results obtained for sharing practices.

Galton's problem

Concerning the power of statistical inference in cross-cultural studies, Galton's problem (i.e., that cultural variables may or may not be independent from one another) should also be taken into consideration; what Galton's problem points out is that common ancestry or diffusion may make sample correlations more significant statistically than they would otherwise be, (see (Ember and Ember, 2000), Galton's Problem in cross-cultural research). Its main implication is the need to be cautious when drawing inferences from statistical cross-cultural studies, since if variables are not independent, they can give rise to spurious correlations.

With regard to the present case study, as only a positive result was obtained for the relationship between the percentage of dependence on animal husbandry and status distribution, the only precision to be made (as previously pointed) is that our results suggest the existence of such relationship, but do not provide strong evidence of it.

Eventually, we would like to conclude with some brief reflections on cross-cultural studies. There has been much debate around cross-cultural research and the legitimate or illegitimate nature of this type of studies (Ember and Ember, 2001). Four are the main objections argued: the supposed incomparability of cultural traits (cultures are unique and therefore not comparable), the supposed incomparability of units of analysis (societies), the supposed impossibility of unbiased sampling (ethnographic and archaeological studies are inextricably linked to systematic biases related to the very different perspectives adopted by different data collectors over time, as well as in different cultural contexts) and Galton's problem (Ember and Ember, 2000). The answers to these four objections can also be found in (Ember and Ember, 2000), where, in overall terms, what the authors claim is that it is easy to measure variables cross-culturally even if the data (ethnographic, archaeological) are qualitative, and that it is possible to sample the universe of human societies in an unbiased way so that test results can be generalized to all of human experience. In short, their main conclusion in (Ember and Ember, 2000, 2001) is that cross-cultural analysis enables to go beyond case-related particulars and provides results explaining global phenomena that are more generally valid and more easily generalizable than those coming from single-case studies, as no type of research except for cross-cultural studies can say that a result is likely to be true for the world, because only cross-cultural research attaches a worldwide probability to a result.

Now that we are in the era of big data, data analysis and data mining, the software available renders multivariate analysis an easy task. Therefore, the best we can do to achieve a deep understanding of cultural phenomena is to go beyond the particularities of each case and to test our theories cross-culturally. Consequently, even if the use of a continental scale of analysis has previously been argued as a plausible explanation for the lack of relationships found in this work, it is clear that further analyses similar to the present one are needed to consolidate a research line devoted to increasing our global knowledge of social phenomena and to reaching empirically supported, theoretically laden generalizations.

CONCLUSIONS

The overarching aim of this work was to formally explore from a cross-cultural perspective the influence that ecological and economic conditions may have on the development of food sharing practices in human societies. The main results obtained from this study may be summarised as follows:

- At a continental scale focused on the Americas and Siberia, a generalised lack of statistically significant relationships between food sharing practices and the considered socio-ecological variables was found across all methodologies implemented. A single positive result was obtained, which suggested the possible existence of a relationship between the percentage of dependence on animal husbandry and the presence of sharing practices dominated by status distribution.
- The hypothesis that food sharing practices of geographically closer populations may be more similar is not supported either by any of the analyses conducted.

Nevertheless, these results do not exclude the possibility that at a different scale of analysis other relationships may exist, as we know that the chosen scale, the systematic description adopted, and the approach selected, may have had an impact on the strength of the patterns that we were able to identify. Therefore, even if it is out of the scope of the present paper, the use of a different scale of analysis or the inclusion of the stages and/or the order of performance of each basic sharing practice would be worthwhile future research issues.

Furthermore, it would be also strongly recommendable to account for the effects of other sociocultural variables (such as social organization, differences between matrilineality and patrilocality, gender issues, etc.), as well as for the effects of cultural transmission and cultural diffusion processes. Regarding this second aspect, it would be interesting to investigate cultural inheritance and demic migration models through common ancestry between population pairs, to check their relative impact on the observed distribution of food sharing practices.

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SUPPORTING INFORMATION

S1 TABLE. BINARY CODIFICATION OF THE PRESENCE/ABSENCE OF THE BASIC SHARING PRACTICES IN THE SHARING SEQUENCES OF THE 22 SSSS CONSIDERED.

https://doi.org/10.1371/journal.pone.0216302.s001

(DOCX)

S2 TABLE. P-VALUES FOR THE DIFFERENT INDEPENDENT TWO-SAMPLE STATISTICAL TESTS.

The cases where the T-test was applied are in white, those where only the Wilcoxon-Mann-Whitney test was applied are in green, and in light pink we can find the three P-values obtained for Fligner-Policello (in bold), Brunner and Munzel (in italics) and Wilcoxon-Mann-Whitney (in ordinary font) respectively.

https://doi.org/10.1371/journal.pone.0216302.s002

(DOCX)

S3 TABLE. MEAN SQUARED ERROR PER FOLD OBTAINED FOR THE DIFFERENT REGRESSION MODELS IMPLEMENTED.

Mean value over ten folds, standard deviation and standard error in the shadowed rows of the table.

https://doi.org/10.1371/journal.pone.0216302.s003

(DOCX)

S4 TABLE. COMPLETE DATABASE WITH ALL VARIABLES CONSIDERED (RAW DATA).

https://doi.org/10.1371/journal.pone.0216302.s004

(XLSX)

S1 APPENDIX. CLARIFICATION OF SOME CONCEPTS RELATED TO THE SOCIOECOLOGICAL VARIABLES SELECTED.

https://doi.org/10.1371/journal.pone.0216302.s005

(DOCX)

S2 APPENDIX. MULTIPLE COMPARISON CORRECTIONS.

https://doi.org/10.1371/journal.pone.0216302.s006

(DOCX)

S3 APPENDIX. HHG CORRECTED P-VALUES IN ASCENDING ORDER.

https://doi.org/10.1371/journal.pone.0216302.s007

(DOCX)

6. LET’S GO FISHING: A QUANTITATIVE ANALYSIS OF SUBSISTENCE CHOICES WITH A SPECIAL FOCUS ON MIXED ECONOMIES AMONG SMALL-SCALE SOCIETIES

Virginia Ahedo, Débora Zurro, Jorge Caro, and José Manuel Galán

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ABSTRACT

The transition to agriculture is regarded as a major turning point in human history. In the present contribution we propose to look at it through the lens of ethnographic data by means of a machine learning approach. More specifically, we analyse both the subsistence economies and the socioecological context of 1290 societies documented in the Ethnographic Atlas with a threefold purpose: (i) to better understand the variability and success of human economic choices; (ii) to assess the role of environmental settings in the configuration of the different subsistence economies; and (iii) to examine the relevance of fishing in the development of viable alternatives to cultivation. All data were extracted from the publicly available cross-cultural database D-PLACE. Our results suggest that not all subsistence combinations are viable, existing just a subset of successful economic choices that appear recurrently in specific ecological systems. The subsistence economies identified are classified as either primary or mixed economies in accordance with an information-entropy-based quantitative criterion that determines their degree of diversification. Remarkably, according to our results, mixed economies are not a marginal choice, as they constitute 25% of the cases in our data sample. In addition, fishing seems to be a key element in the configuration of mixed economies, as it is present across all of them.

INTRODUCTION

THE ORIGINS OF AGRICULTURE

The Origins of Agriculture (OA) is a mainstay of archaeological research, being the transition to farming regarded as one of the major developments in our past (Winterhalder and Kennett, 2006; Fuller, 2010; Zeder, 2015; Smith, 2016). Notwithstanding, after more than a hundred years of research on the OA, we are only just beginning to understand the details of the process (Douglas Price and Bar-Yosef, 2011), remaining plenty of questions unanswered and being the topic still considered one the most relevant scientific challenges for Archaeology (Kintigh et al., 2014).

Even though the adoption of agriculture has often been described as a rapid, unidirectional and inexorable process, the vast expansion of knowledge on the OA of the last two decades has shown that it is a complex phenomenon that encompasses a continuum of plant and animal management strategies; such a continuum frequently extended over long periods of time and involved an intricate interplay of environmental, social and cultural factors (Larson et al., 2014). Therefore, the OA is no longer considered as a single monolithic research question, being now recognised as a higher order research domain comprising a wide range of different research questions, datasets, scales of analysis and analytical and theoretical approaches (Smith, 2015).

The most outstanding questions within the OA research field include its chronology and geography, as well as its causes, pace of development and spread, being all aspects deeply intertwined. Despite the existence -at a high level of detail- of almost as varied approaches to these questions as researchers writing about them, in more general terms, the OA state of play can be summarised around two main explanatory frameworks: traditional universalist explanations and more recent alternatives.

TRADITIONAL UNIVERSALIST EXPLANATIONS

As the adoption of agriculture occurred almost simultaneously in many different regions of the world, it has traditionally been explained in universalist terms, i.e., a single universal cause is proposed as the lever of the OA. The most renowned universalist prime-mover explanations may be summarised around three main paradigms:

(i) The superiority of agriculture as a mode of production, irrespective of circumstances. Agriculture -a highly desirable development whose advantages were self-evident- would have been automatically adopted in favourable ecological conditions once the necessary knowledge -the limiting factor- had been reached (Caldwell, 1977). Within this framework, growing agriculturalist populations would have colonised new territories, absorbing or displacing local hunter-gatherer groups, and making them adopt agriculture rapidly (Darwin, 1868; Childe, 1928; Braidwood, 1958; Ammerman and Cavalli-Sforza, 1971, 1984). This, in turn, would have laid the ground for a series of socioeconomic changes that later in time resulted in urbanization processes and the emergence of civilisations (Harlan, 1992; Tanno and Maeda, 2017; Fuller and Stevens, 2019).

Accordingly, this first approach encompasses four main correlates that have long influenced the most widespread conception of the OA: (1) a conceptual dichotomy between “two mutually incompatible ways of life” (Zvelebil et al., 1986): hunting and gathering on the one side, agriculture on the other, with no intervening options (Williams and Hunn, 1982). Intermediate positions between the two are regarded as transitory, short-lived intermediate stages from one steady state to the other; over the long term, the great majority of populations are assumed to tend either to maintain a hunter-gatherer subsistence economy or to embrace agriculture, presenting a U-shaped distribution to the relative proportions of gathered/hunted versus produced food in the diet (Bellwood, 2004; Bellwood and Oxenham, 2008). (2) The notion that the agricultural transition was a radical and rapid switch in human evolution, arising from an express domestication once the necessary knowledge was acquired (Williams and

Hunn, 1982; Zvelebil, 1996; Lasse Sørensen, 2014), what enabled its consideration as a "revolution": the Neolithic Revolution (Childe, 1951; Weisdorf, 2005; Simmons, 2007). (3) The conception of the adoption of agriculture as a "point of no return" (Tanno and Maeda, 2017); for those hunter-gatherer societies becoming agriculturalists, there would be no turning back unless they are compelled by environmental downturn or increased mortality (Bellwood and Oxenham, 2008). And (4) a view of human history totally biased towards a classical idea of progress in which agriculture is clearly prioritised against hunting and gathering (Weisdorf, 2003, 2005; Fuller and Stevens, 2019), hence being hunter-gatherers stereotyped as inherently simple and agriculturalists as culturally complex (Bender, 1985b; Bharucha and Pretty, 2010).

(ii) SET[1]-based explanations for initial domestication. This second paradigm is based on the core assumption of unidirectional adaptation -environments change and organisms adapt, never vice versa (Williams, 1992)-; more precisely, a population-resources imbalance is proposed as a direct or underlying cause of the transition to farming. Such an imbalance could have originated either on the supply side, the demand side or both (Binford, 1968; Flannery, 1969). Thereupon, domestication, intensification and/or the exploitation of suboptimal resources would have emerged as an adaptive response to the resource pressure induced by demographic changes in the form of a local (Hassan, 1981; Binford, 1983) or a global (Cohen, 1977, 2009) population increase, and/or by environmental changes such as a decline in resource availability (Piperno, 2006, 2011; Zvelebil, 1981; Zvelebil and Rowley-Conwy, 1984) and/or climatic variations like the Pleistocene-Holocene climatic transition -which resulted in warmer, wetter conditions, a significant reduction in climate fluctuations, and a 33% increase in atmospheric CO_2- (Sage, 1995; Bar-Yosef, 1998, 2011; Richerson et al., 2001; Gupta, 2004; Feynman and Ruzmaikin, 2007; Willcox et al., 2009; Ferrio et al., 2011).

It is important to recall that the key assumption of this second paradigm is that hunter-gatherers would only have become agriculturalists under pressure, as farming is usually more labour-intensive, backbreaking and time-consuming than hunting and gathering (Binford, 1968), often leading to no immediate change in quality of life (Binford, 1968; Lee, R. B., & DeVore, 1968; Lee, 1972, 1979).

(iii) Social hypothesis. Under this paradigm, the onset of agriculture would have been motivated by social forces in stress-free scenarios. More precisely, a set of 'social disequilibrium models' (Sahlins, 1972a; Godelier, 1977; Bender, 1978, 1985b, 1985a) proposes that farming would have been embraced to maintain social control, or in the struggle for power, spouses and/or status (Zvelebil et al., 1986); this, in turn, would have resulted in the emergence of inequality and hierarchical societies.

[1] SET – Standard Evolutionary Theory

MORE RECENT ALTERNATIVES DERIVED FROM EE, NCT AND INTEGRATIVE PROPOSALS

Recent explanatory approaches are either derived from Evolutionary Ecology (EE) -inclusive of Human Behavioural Ecology (HBE)- (Winterhalder and Kennett, 2006, 2009; Codding and Bird, 2015; Gremillion, 2019), from Niche Construction Theory (NCT) (Smith, 2011a, 2015, 2016; Zeder, 2015, 2016), or from integrative approaches comprising EE, NCT and models of cultural transmission and gene-culture coevolution that envisage all the perspectives involved as complementary, synergetic and broadening each other (Broughton et al., 2010; Gremillion et al., 2014; Freeman et al., 2015; Mohlenhoff et al., 2015; Stiner and Kuhn, 2016; Mohlenhoff and Codding, 2017; Piperno et al., 2017; Gremillion, 2019).

EE is a selectionist, neo-Darwinian high-level theoretical framework that provides a well-defined set of general concepts, assumptions and analytical tools -such as optimisation theory- for the study of specific adaptations through the lens of the interaction between evolutionary forces and ecological variables. One of its subfields, HBE, which investigates human behaviour in relation to ecological conditions and assesses the different behavioural strategies in terms of fitness (Foley, 1985; Winterhalder and Kennett, 2006), has already made substantial contributions to OA research (Mulder, 2005). In this regard, particularly famous is the Diet Breadth Model (DBM), according to which human groups are supposed to have a list of all the resources in their environment ranked in descending order of net caloric return, being delayed-return strategies -such as resource management and production- only embraced when immediate-return alternatives are not productive enough (MacArthur and Pianka, 1966; Schoener, 1971; Winterhalder and Kennett, 2006; Piperno et al., 2017). According to the DBM, at the dawn of agriculture, a resource depression would have forced the inclusion in the diet of previously ignored resources such as the wild ancestors of present domesticates (small to medium-sized mammals, seeds and tubers), resources otherwise falling beneath the “optimal diet” boundary of human societies world-wide (Gremillion et al., 2014).

On its part, NCT postulates that organisms are capable of modifying their own evolutionary trajectories -and those of other species- by actively engineering their living environments, which can provide them with evolutionary advantages (Odling-Smee et al., 2003). Thence, according to NCT domestication arose from large-scale human efforts at ecosystem enhancement in the absence of any sort of population-resources disequilibrium (Smith, 2016). More specifically, NCT representatives (Smith, 2007, 2011b, 2015; Zeder, 2012, 2016) consider that agriculture would have emerged in climatically stable resource-rich scenarios -usually near water-, where small-scale societies would have established small semi-permanent to permanent central settlements, and within which a wide range of plant and animal species would have been comprehensively auditioned over many generations, evolving just a subset of them into domesticates (Smith, 2016).

Over the last few years, the increasing wealth of data on the OA has evidenced that the transition to farming was characterized by a great variability across time and space, i.e., that the different world regions followed independent developmental pathways, being each one of them shaped by a number of complex and locally contingent factors, and generally extending over long periods of time (Zeder and Smith, 2009; Gremillion et al., 2014). As a result, considerable controversy has emerged regarding the utility of the different explanatory approaches for the OA, existing to this day no consensus on which approach is most appropriate; in fact, the OA community continues to be characterised by a lack of consensus in many respects (Douglas Price and Bar-Yosef, 2011), with just a few major areas of agreement that may be summarised as follows:

- At least eleven world regions have been identified as independent centres of domestication, but several more have been suggested (Larson et al., 2014). In addition, each major independent region would have also included multiple loci for domestication (Barker, 2006; Douglas Price and Bar-Yosef, 2011).
- The unforeseen synchronicity in the timing of the first domesticates around the end of the Pleistocene (Aiello, 2011; Douglas Price and Bar-Yosef, 2011); more precisely, the earliest morphologically domestic cereals date to about 12,000 – 11,000 cal years B.P. (Larson et al., 2014). However, it is not straightforward to identify when cultivation started, as new evidence is pushing the existence of pre-domestic cultivation -gathering of wild cereals and small-grained grasses- back to the late Pleistocene (Weiss et al., 2004a; Willcox et al., 2009; Nadel et al., 2012).
- The emergence of agriculture took place in resource-rich areas -instead of marginal ones as previously thought-, which enabled domestication experiments and the sustained auditioning of different plant and animal species (Smith, 2007; Aiello, 2011). In fact, the cradles of agriculture are now regarded as the regions to which the most numerous and profitable future domesticates were native (Diamond, 2002).
- The need to distinguish between OA, domestication and agriculture (Douglas Price and Bar-Yosef, 2011; Larson et al., 2014). Albeit it is extremely difficult to define clear thresholds that separate the different stages, there are two confirmed delay phenomena that cannot be disregarded: (i) the existence of long periods of species manipulation/cultivation before the emergence of domestication traits -fixing the non-shattering spikelet in wheat, barley and rice took for instance up to ~2,000-4,000 years (Fuller et al., 2014)-, and (ii) the millennial-scale delay between initial domestication attested through morphological evidence and the development of fully agricultural economies (Smith, 2001; Zeder, 2011). Hence, domestication is not an automatic outcome of manipulation, and neither is agriculture of domestication, existing a vast middle-ground of long-term subsistence economies in between.
- The abandonment of traditional dichotomies between wild and domesticated, hunting-gathering and agriculture, etc., in favour of a continuum of plant and animal management strategies (Douglas Price and Bar-Yosef, 2011; Gremillion et al., 2014). Such a continuum would stretch from hunting and gathering on the one margin, to fully agricultural societies on the other, encompassing all the above-mentioned middle-ground possibilities, and making no assumptions of progress or unidirectionality between them.

- Consistent with the above, the development of agriculture would have been a drawn-out process rather than a revolution (Zvelebil, 1981, 2001; Winterhalder and Kennett, 2006; Fuller et al., 2015; Bueno Ramírez and de Balbín Behrmann, 2016).

In addition to the foregoing, a significant number of OA researchers agree that single causal scenarios based on prime movers fall short (Zeder, 2006, 2015; Zeder and Smith, 2009; Gremillion et al., 2014; Larson et al., 2014). Clearly, the amelioration of climates at the end of the Pleistocene acted as a trigger; however, other relevant factors such as human demography, social systems and the biological characteristics of the auditioned species were operating simultaneously in tightly interconnected networks, thus being not possible nor convenient to select just one of them as the only cause. As a consequence, current approaches revolve around broader explanatory frameworks that try to integrate both the interplay of the different factors (Douglas Price and Bar-Yosef, 2011; Larson et al., 2014; Zeder, 2015) and distinct theoretical approaches such as HBE and NCT (Broughton et al., 2010; Mohlenhoff et al., 2015; Mohlenhoff and Codding, 2017; Piperno et al., 2017; Gremillion, 2019).

THE VAST MIDDLE-GROUND

In the previous section, we concluded by underscoring the inherent complexity of the transition to farming, which stems mainly from the protracted nature of the process, its marked variability across time and space, the multitude of factors involved at both the macro and micro scales, the intricate nature of the diverse middle ground, and the subsequent long-standing debates on the suitability of the different explanatory approaches. As pointed by Smith (2001), from all the factors mentioned, the middle ground is probably the most largely neglected one, a fact that continues to hamper significantly our current understanding of the agricultural transition. Hence, in the present paper we intend to shed light on what the middle ground may have looked like. Given that the interest of the present contribution may be best understood in the light of what is known about the middle ground thus far, here we proceed to cover some of the key aspects.

The middle ground refers to the conceptual territory between hunting, gathering and fishing on the one side, and agriculture and husbandry on the other. In accordance with the classic dualistic epistemology, foragers had no domesticates, and all human societies with domesticates had agriculture, being the transition between the two regarded as a mere shift (Smith, 2001). Consistently, the middle ground has traditionally been regarded as some sort of hodgepodge of all the subsistence economies not meeting the criteria to be considered either hunter-gatherers or agriculturalists. Nevertheless, as discussed earlier, there is a global consensus that such dichotomic approaches are both insufficient and inefficient for several reasons, outstanding among which are (i) the difficulty of defining “hunter-gatherers” and “agriculturalists”: over the years, numerous definitions have been proffered -some of them inspired in real referents coming from Ethnography and/or Archaeology, whose attributes have been established as diagnostic-; however, hitherto no single definition is considered to have a global or universal applicability (Terrell et al., 2003; Smith, 2006). (ii) The prolonged nature of the transition to agriculture, which indeed extended over millennia, hence having had to encompass many successful long-term subsistence alternatives that are fully disregarded in the binary approach (Smith, 2001). And (iii) its implicit strait-ahead linear sense, which depicts the transition as an evolutionary process irreversibly leading to agriculture (Bogucki, 1995). Therefrom, while the conceptual dichotomy can still be useful as chronological markers that delimit the extremes of the middle ground, it is also quite harmful, since it blurs and oversimplifies the multiple changes in subsistence behaviour that must have occurred during the Holocene in many different regions of the world. Moreover, even if different adjectives such as “complex” hunter-gatherers, “affluent” foragers, “incipient” agriculturalists, etc., have been used in an attempt to differentiate middle-ground strategies, those expressions still hold the imprint of the binary conceptualisation, and implicitly displace in-between societies to one margin or the other, hence concealing again the relevance of the middle ground in its own right.

More recently, different authors have addressed the middle ground in various ways that transcend the dichotomous perspective. In overall terms, their proposals can be grouped around two main approaches: compartmental schemes and non-classificatory perspectives. As stated by Smith (2001), compartmental schemes are aimed at “identifying and defining categories of human-plant and human-animal interaction” characteristic of a given subset of middle-ground societies. When taken together, all these interaction categories “form a continuum of increasing human intervention or involvement in the life cycle of targeted species […] that encompasses the landscape that lies between hunting-gathering and agriculture”.

Over the years, many scholars have adopted the compartmental approach: see for instance, Ford (1985), Harris (1989, 1990, 1996b, 1996a), Higgs (Higgs, 1975) and Zvelebil (1995, 1996) -among others-; however, the most renowned of all compartmentalists is decidedly Bruce D. Smith thanks to his proposal in (Smith, 2001) that if the binary categories food procurement and food production are maintained, the latter should be split into three main sub-categories: *low-level food production without domesticates*, *low-level food production with domesticates* and *agriculture*. Smith encompasses under food production all human actions aimed at intervening in the life cycle of targeted species, regardless of the presence or absence of domestication traits. Within the food production territory, subsistence strategies reliant on domesticates for less than a 30%-50% of the annual caloric intake are considered low-level food production, while those above such boundary are deemed fully agricultural economies. Regarding the partition between low-level food production without domesticates and low-level food production with domesticates, as their name suggests, the boundary marker is domestication, i.e., the presence of morphological/genetic changes associated with the domestication syndrome. Nonetheless, as recurrently highlighted by Smith (2001), the definition of boundaries is an extremely troublesome task, since manifold management strategies have been documented across all categories at different intensity levels. Therefore, the relevance of Smith’s proposal is not to be found in the robustness of the definition of boundaries, but on the creation of the low-level food production category and its two subcategories; a conceptualisation that serves to highlight the importance of such a diverse array of stable subsistence strategies, whose persistence attests to their versatility and success in a wide range of different socioenvironmental contexts.

Several ensuing publications incorporated Smith’s conceptualisation of the middle-ground either making use of the term *low-level food production* (Rowley-Conwy and Layton, 2011;

Zeder, 2011, 2015; Jiao, 2016) or developing similar ones such as: *low-level food resource producers* (Crawford, 2006, 2011) or *mixed economies* (Tharakan C., 2003; Winterhalder and Kennett, 2006; Greaves and Kramer, 2014; Burnsilver et al., 2016; Svizzero, 2016a, 2016b). Notwithstanding, other authors such as Terrell et al. (2003) have argued that instead of a classification system whose inter-category boundaries are difficult to establish, it would be more appropriate to describe and compare subsistence strategies without first having to label them. Hence, they proposed the "provisions spreadsheet", an interactive matrix of species and harvesting tactics intended to overcome restrictive definitions of domestication, and to accommodate the known diversity of human subsistence practices. Notably, the provisions spreadsheet covers four different aspects: goal (food or raw materials), primary variables (resource breadth and their yield, accessibility and reliability), secondary variables (behavioural or environmental manipulation skills necessary to exploit those resources) and observations, to faithfully reflect the particularities of each socio-economic strategy and of the environment within which they develop(ed).

To this day, no-one of the two approaches has proven to be better than the other. However, this is not necessarily a problem, as both proposals serve to place on the middle ground the emphasis it deserves, and highlight the difficulty of establishing clear-cut frontiers between the different subsistence possibilities. In fact, in the last decades, plenty of empirical evidence -both ethnographic and archaeological- is showing that a great deal more research is needed to understand the different subsistence combinations, and to unravel the particulars of the middle ground. Regarding the most outstanding recent findings on the middle ground, particular mention must be made of the innate complexity of hunter-gatherer resource management techniques, the sophistication of complex hunter-gatherer societies and the relevance of mixed economic choices.

As regards hunter-gatherer complexity, several recent contributions have served to emphasise both the diversity inherent in hunter-gatherer subsistence practices, and the great variety of their socio-political systems (Sassaman, 2004; Kim and Grier, 2006; Sapignoli, 2014). One of the major advances has certainly been the recognition that no human societies are *simple* by definition, as even the smallest hunter-gatherer societies present intricate social relationships, and elaborated economic solutions that comprise scheduling, mobility, task differentiation, gender division of labour, etc. (Kim and Grier, 2006). In addition, the engagement in efforts at landscape engineering such as regular burning, tending, tilling, transplanting, weeding, sowing and selective harvesting has been documented for both hunter-gatherers and low-level food producers, which supports the existence of a wide spectrum of hunter-gatherer and low-level-food-production subsistence strategies without clear frontiers between them (Harris and Hillman, 1989; Ames, 2014; Svizzero, 2016a).

Henceforth, hunter-gatherers are no longer regarded as failed agriculturalists living in marginal environments; quite the opposite, at present, hunting-gathering and low-level food production are conceptualised as a broad range of successful socioeconomic solutions characterised by their flexibility, resilience and adaptability to very different contexts (Sapignoli, 2014).

As regards mixed economies, plenty of past and present empirical examples attest to their great variety and endpoint solution status. In the context of Archaeology and Prehistory, mixed economies tend to refer to economies developed during the Mesolithic and the Early and Middle Neolithic. Although some publications refer to mixed economies whenever fishing complements hunting and gathering (Palmisano et al., 2017), most researchers designate under mixed economies a combination of foraging (hunting, gathering and/or fishing) with different food-production activities such as farming at different intensity levels and/or small-scale herding (Madsen and Simms, 1998; Robb, 2007; Svizzero and Tisdell, 2014; Medina et al., 2016); more precisely, the most widespread definition of a mixed economy is probably the one proffered by Winterhalder and Kennet (2009)#as “an economy (…) that includes, in long-enduring combinations, both foraging and the low-level use of cultivars or domesticates“.

Some of the most paradigmatic archaeological examples of mixed economies include the Jomon -Japan- and Chulmun -Korea-, whose resource procurement strategies included hunting, gathering, fishing and resource production strategies ranging from annual plant encouragement and tree management, to domestication of particular species and cultivation of others (Crawford, 2008, 2011; Crawford and Takamiya, 2008; Lee, 2011); the Okhotsk -preceded in time by the Jomon- who hunted, gathered, raised pigs and had a few crops (Crawford, 2011); the peoples from the Northwest Coast of North America -typically classified as complex hunter-gatherers- who were strongly reliant on mariculture and conducted plenty of resource management activities to sustain and enhance both marine and plant resources -beach clearance, clam and root gardening, transplanting salmon eggs, tree modification, landscape burning, soil tilling, etc.- (Erlandson, 2001; Turner et al., 2013; Lepofsky et al., 2015; Mathews and Turner, 2017); and the late Prehispanic peoples from Sierras of Córdoba -Argentina-, whose subsistence economy was a mix of small-scale farming and broad-scale foraging (Medina et al., 2016).

In the ethnographic record, some of the most well-known examples of mixed economies include the Ituri forest foragers of the Democratic Republic of Congo -who engage in partnership relationships with agriculturalists-, the Agta from the Philippines -famous for their exchange of meat for rice-, the savanna Pumé -a Venezuelan mobile hunter-gatherer society that incorporates manioc cultivation as a fallback strategy- (Greaves and Kramer, 2014), the Mlabri -skilled hunter-gatherers now living in north-eastern Thailand and the western Laos, who establish symbiotic trading relationships with more settled groups- (Svizzero and Tisdell, 2015), and present-day indigenous communities in the Arctic -whose economy combines foraging with trade or other economic activities such as full-time or part-time paid work, seasonal labour, craft-making, commercial fishing and/or tourism- (Svizzero and Tisdell, 2015; Burnsilver et al., 2016; BurnSilver and Magdanz, 2019; Wenzel, 2019).

It is clear from the foregoing that the study of the middle ground is key to understand prehistoric societies in general, and the transition to agriculture in particular. Remarkably, both in the ethnographic and archaeological records, we count with plenty of examples that illustrate the whole economic variability that human societies have implemented around the globe for millennia. In this regard, it is important to recall that even if Ethnography and Archaeology tend to deal with different time periods and rythms (Cunningham, 2009), and being fully aware that available ethnographic information does not necessarily and directly inform about prehistoric societies, the fact is that ethnographic data allows to test archaeological theory by confronting it with real case studies. Concretely, as regards subsistence strategies, ethnographic examples enable to identify which economic choices are plausible, and in which contexts they are effectively taking place, thus contributing to a general theory of human and social behaviour that can be used as a frame of reference for prehistoric studies (Skibo, 2009; Binford, 2019).

RESEARCH PROPOSAL

From a methodological perspective, our contribution is framed within the increasingly relevant research line of integration, mining, analysis and interpretation of archaeological, ethnographic and anthropological data to explore global patterns through advanced computer-based approaches (Fischer et al., 2013; Kirby et al., 2016; Fischer and Ember, 2018). In particular, in the present work we intend to explore the middle ground by means of a comprehensive analysis of the subsistence strategies of 1290 societies extracted from the Ethnographic Atlas (Ethnographic Atlas, 1962; Murdock, 1967; Gray, 1998), which are either historical or ethnographically documented. The purpose of such an approach is twofold: (i) increasing our understanding of the different combinations of subsistence strategies that have been developed across the world over time; and (ii) providing new perspectives from which to explore prehistoric economies, the persistence of hunter-gatherer(-fisher) economies, and the agricultural transition. Note that we are not aiming at establishing direct formal analogies between our data and Prehistory, but at better understanding human economic choices, the contexts in which they develop, and their success in the long term. Therefore, our study can be considered to belong to the theory-building realm, and it may help to look at prehistoric economies in a new light, and/or to hypothesise in a different way about particular archaeological contexts.

More precisely, we are interested in the following research questions:

1. **Regarding subsistence strategies, are all combinations viable or do specific patterns exist?** The rationale behind this question is to be found in the fact that human societies configure their economic choices so as to procure enough food for group survival and a balance of required nutrients; such a balance is usually attained by including in the diet different foodstuffs coming from both the plant and animal realms. However, the selection of those foodstuffs is not a trivial undertaking, as the choice is influenced by a series of variables including -among others- resource availability (their temporal and spatial distribution), population density, the degree of technological development, etc. In other words, human subsistence choices both depend on and modify the carrying capacity of the whole socio-ecological system, being therefore relevant to explore if all combinations are feasible or if only a subset of them are successful. In this line, it will also be of interest to look into the possible complementary or exclusive relationships that could exist between the different subsistence strategies.

2. **The role played by ecological settings in the configuration of the different subsistence economies**, as they may prevent specific economic choices while fostering

others. For instance, in some settings the carrying capacity can be increased through greater labour investment and/or diversification without the need to adopt new strategies, while in others intensification is unfeasible because of environmental reasons (e.g. agriculture is impracticable in Arctic areas and deserts). Therefore, -and without falling into environmental determinism-, one may expect the association of specific economic choices with certain ecosystems (or biomass richness), hence being of interest to look for those relationships in empirical data.

3. **The role of fishing in the development of viable alternatives to cultivation.** Coastal and riverine areas constitute bountiful ecosystems with a specific behaviour regarding carrying capacity and resource availability. In these contexts, the only limitations are a priori technological and/or related to biogeographical constraints, since resources are abundant and resource restoration is in principle not problematic. Henceforth, in such settings, the development of ad hoc technologies expedited the emergence of successful long-term subsistence economies that, in some cases resulted in sedentism, large population densities, intensive exploitation of resources and increased social complexity, traits long assumed to be exclusive of agricultural societies (Ames, 2014). Thus, the study of economies in which fishing has a significant weight may be useful to understand non-agricultural successful economic choices and/or to shed light on the middle ground.

MATERIALS AND METHODS

DATA SOURCES

All data used in the present study were extracted from the Database of Places, Language, Culture, and Environment -D-PLACE- (Kirby et al., 2016) accessible at https://d-place.org/. In words of its creators, D-PLACE is “an attempt to bring together the dispersed corpus of information describing human cultural diversity” (D-PLACE - About), being its main goal to facilitate cross-cultural analyses. More specifically, D-PLACE integrates information from multiple datasets and presents it in a unified and consistent manner.

The sample of societies selected is that of the Ethnographic Atlas (EA) (Ethnographic Atlas, 1962; Murdock, 1967; Gray, 1998), which in its original form includes up to 1291 societies ranging from small hunter-gatherer groups to societies with complex agricultural economies. However, in the present contribution we reduced the EA sample size to 1290, since that is the number of societies for which we had information on subsistence strategies. It is important to note that while these societies are globally distributed, the EA has especially good coverage of Africa and western North America (D-PLACE - Dataset Ethnographic Atlas). As regards the focal time period, the different time frames and the percentages of EA societies falling under each of them can be found in Table 11.

Table 11. Focal time periods of the societies documented in the EA.

Focal time period	% of EA societies
Before 1800	3
1800 – 1899	27
1900 – 1950	66
After 1950	2

From Table 11 it becomes clear that the time span covered is quite circumscribed. This aspect is particularly convenient, since it avoids problems associated with longer time frames, namely changing ecological and social conditions, different occupations of the same site over time, long-term transitions in subsistence economies, social organisation, etc.

The different subsistence-related and socio-ecological variables used in this work and the datasets from which they were extracted are detailed in Table 12. Note that the column Data type indicates if the variable is originally continuous, categorical or ordinal in D-PLACE. Subsequent transformations of the variables are duly explained in the corresponding Rmarkdowns available at the GitHub repository of the paper: https://github.com/Virahe/Lets-go-Fishing.

Table 12. Variables selected for the present study from the different sources available at D-PLACE.

Dataset	Variables			
	D-PLACE variable ID	Short name	Description	Data type
Ethnographic Atlas (*Ethnology*, 1962;	EA001	% dependence on gathering	Percentage of dependence on the gathering of wild plants and small land fauna, relative to other subsistence activities.	Ordinal

Gray, 1998; Murdock, 1967)	EA002	% dependence on hunting	Percentage of dependence on hunting, including trapping and fowling, relative to other subsistence activities.	Ordinal
	EA003	% dependence on fishing	Percentage of dependence on fishing, including shellfishing and the pursuit of large aquatic animals, relative to other subsistence activities.	Ordinal
	EA004	% dependence on husbandry	Percentage of dependence on animal husbandry, relative to other subsistence activities.	Ordinal
	EA005	% dependence on agriculture	Percentage of dependence on agriculture, relative to other subsistence activities.	Ordinal
	EA028	Agriculture intensity	Intensity of cultivation. Levels: no agriculture, casual, extensive/shifting, horticulture, intensive, intensive irrigated.	Categorical
	EA029	Major crop type	Principal type of crop cultivated. Levels: no agriculture, non-food, vegetables, tree-fruits, roots/tubers, cereals.	Categorical
	EA030	Settlement patterns	The prevailing type of settlement pattern. Levels: nomadic, seminomadic, semisedentary, impermanent, dispersed homesteads, hamlets, villages/towns, complex permanent.	Categorical

	EA033	Jurdisdictional hierarchy beyond local community and political complexity	The number of jurisdictional levels beyond the local community, with 1 representing the theoretical minimum (none/autonomous band or villages) and 4 representing the theoretical maximum (villages nested within parishes, districts, provinces, and a complex state). This variable also provides a measure of political complexity, ranging from 1 for stateless societies, through 2 or 3 for petty and larger paramount chiefdoms or their equivalent, to 4 or 5 for large states. Imposed colonial regimes are excluded.	Ordinal
	EA039	Plow cultivation	Indicates whether or not animals are employed in plow cultivation, and whether plow cultivation is aboriginal or dates to the post-contact period. Levels: absent, not aboriginal but present, present.	Categorical
	EA040	Type of domestic animals	The predominant type of animals kept. Levels: absence or near absence, pigs, sheep/goats, equine, deer, camelids, bovine.	Categorical
	EA041	Milking	Indicates whether or not domestic animals milked. Levels: absence or near absence, more than sporadically.	Categorical

	EA202	Population size	Population of ethnic group as a whole. Note that source differs by society; EA bibliography is source where possible, otherwise Ember (1992).	Continuous
Jenkins et al. (2013)	AmphibianRichness	Amphibian richness	Number of coexisting amphibian species.	Continuous
	BirdRichness	Bird richness	Number of coexisting bird species.	Continuous
	MammalRichness	Mammal richness	Number of coexisting mammal species.	Continuous
Kreft and Jetz (2007)	VascularPlantsRichness	Vascular plant richness	Number of coexisting vascular plant species.	Continuous
Moderate Resolution Imaging Spectroradiometer (NASA. Net Primary Productivity (1 month - TERRA/MODIS))	AnnualNetPrimaryProductionVariance	Variance in net primary production per month	Variance in net primary production per month.	Continuous
	MonthlyMeanNetPrimaryProduction	Net primary production per month (grams of carbon uptake per square meter	Net primary production per month (grams of carbon uptake per square meter and land per month).	Continuous

		of land per month)		
	NetPrimaryProductionConstancy	Net primary production constancy	Colwell's (1974) information theoretic index. Indicates the extent to which a climate patterns are predictable because conditions are constant. Varies between 0 (completely unpredictable) and 1 (fully predictable).	Continuous
	NetPrimaryProductionContingency	Net primary production contingency	Colwell's (1974) information theoretic index. Indicates the extent to which a climate patterns are predictable because conditions oscillate in a very predictable manner. Varies between 0 (completely unpredictable) and 1 (fully predictable).	Continuous
	NetPrimaryProductionPredictability	Net primery production predictability	Colwell's (1974) information theoretic index. Indicates the extent to which a climate patterns are predictable due to either constancy or contingency. Varies between 0 (completely unpredictable) and 1 (fully predictable).	Continuous
Terrestrial Ecoregions of the World	Biome	Biome	Classification by Olson et al. (2001) of the earth into fourteen units that host similar formations of plants and animals due to their climates. A single biome can be found over a range of continents.	Categorical
Baseline Historical (1900-1949), CCSM	AnnualMeanTemperature	Mean value of monthly	Mean value of monthly temperature across the year	Continuous

ecoClimate model (Lima-Ribeiro, 2015)		temperature across the year		
	AnnualPrecipitationVariance	Variance in monthly precipitation means	Variance in montly precipitation means	Continuous
	AnnualTemperatureVariance	Variance in monthly temperature means	Variance in monthly temperature means	Continuous
	MonthlyMeanPrecipitation	Mean monthly precipitation in ml/m^2/month	Mean monthly precipitation in ml/m^2/month	Continuous
	PrecipitationConstancy	Precipitation constancy	Colwell's (1974) information theoretic index. Indicates the extent to which a climate patterns are predictable because conditions are constant. Varies between 0 (completely unpredictable) and 1 (fully predictable).	Continuous
	PrecipitationContingency	Precipitation contingency	Colwell's (1974) information theoretic index. Indicates the extent to which a climate patterns are predictable because conditions oscillate in a very	Continuous

			predictable manner. Varies between 0 (completely unpredictable) and 1 (fully predictable).	
	PrecipitationPredictability	Precipitation predictability	Colwell's (1974) information theoretic index. Indicates the extent to which a climate patterns are predictable due to either constancy or contingency. Varies between 0 (completely unpredictable) and 1 (fully predictable).	Continuous
	TemperatureConstancy	Temperature constancy	Colwell's (1974) information theoretic index. Indicates the extent to which a climate patterns are predictable because conditions are constant. Varies between 0 (completely unpredictable) and 1 (fully predictable).	Continuous
	TemperatureContingency	Temperature contingency	Colwell's (1974) information theoretic index. Indicates the extent to which a climate patterns are predictable because conditions oscillate in a very predictable manner. Varies between 0 (completely unpredictable) and 1 (fully predictable).	Continuous
	TemperaturePredictability	Temperature predictability	Colwell's (1974) information theoretic index. Indicates the extent to which a climate patterns are predictable due to either constancy or contingency. Varies between 0 (completely unpredictable) and 1 (fully predictable).	Continuous

METHODS: DATA ANALYSIS

The analysis of the database described in the previous section was performed in two stages:

1. Exploratory data analysis by means of unsupervised learning techniques: Principal Components Analysis and clustering.
2. Supervised learning approach.

The details of the analytical methods applied in each of the two stages are summarised below.

EXPLORATORY DATA ANALYSIS BY MEANS OF UNSUPERVISED LEARNING TECHNIQUES

Unsupervised learning is a subfield of machine learning conceived to look for patterns in a dataset with no predefined response variable, i.e., it is referred to as unsupervised since no output variable guides the analyses (Hastie et al., 2009; James et al., 2013). Under the umbrella of unsupervised learning we find a great variety of methodologies, many of which seek to find relationships either between variables or between observations, hence being generally applied within the framework of exploratory data analysis. Regarding the present contribution, we have drawn on two of the most commonly used unsupervised learning techniques, namely Principal Components Analysis (PCA) and clustering, to address our first research question: *Are all subsistence combinations viable or do specific patterns exist?*

Principal Components Analysis (PCA)

The principal components of a dataset are the dimensions in feature space along which the original data present the greatest variation; these dimensions also define the lines and subspaces that are closest to the data cloud -minimum squared distance-. More precisely, for a dataset X with n observations and p features -all standardised to have mean zero and standard deviation one-, each component is a linear combination of the p features, and all components together constitute an orthonormal basis, which ensures that they are linearly uncorrelated (James et al., 2013).

PCA is the unsupervised learning technique consisting in the computation of the principal components and their subsequent use in understanding the data. It is frequently used for dimensionality reduction and visualisation purposes, since by keeping just the first few principal components and projecting all data points onto them, a low-dimensional representation that captures as much of the information as possible is obtained. Note that the interpretation of the different components is generally conducted by projecting the features on the new low-dimensional space, and by thereafter assessing the correlations between the different features and the corresponding components.

In the context of the present study, we took all the societies in the EA, focused exclusively on the variables ranging from EA001 to EA005, -i.e., the percentages of dependence on gathering, hunting, fishing, husbandry and agriculture, what we have called the subsistence dataset-, and performed PCA to ascertain whether the variability in our data could be explained by just a few components, and if so, to identify which of the variables had a more significant role in explaining such variability.

Clustering

The term clustering encompasses a broad set of algorithms aimed at identifying groups -clusters- in a dataset, so that the observations within each group share some common features, while observations in different groups are quite different from each other (Jain and Dubes, 1988; James et al., 2013). In relation to our first research question, should only a subset of subsistence economies be successful and persistent, it would translate into the data having cluster structure. Therefore, at this stage of the analyses, we took again the subsistence dataset and conducted cluster analysis to ascertain whether it had structure, and if so, to explore the subgroups identified among the observations.

More specifically, we first assessed the clustering tendency of the subsistence dataset following Kassambara (2015), then we opted for the hierarchical clustering methodology (James et al., 2013) -since instead of committing to a specific number of clusters, it results in a dendrogram that allows conducting analysis at different levels of resolution-, and finally, we tried to determine the optimal number of clusters -the height at which to cut the dendrogram- by means of the multiple techniques proposed in (Kassambara, 2015) and consensus clustering (Monti et al., 2003).

Assessment of clustering tendency

A noteworthy issue in clustering analysis is that clustering techniques will return clusters even if the data do not contain any meaningful clusters. Therefore, before applying any clustering algorithm, it is necessary to check whether the data contain non-random structures. To that end, Kassambara (2015) proposes two alternatives:

- **Statistical methods: Hopkins statistic (*H*).** The Hopkins statistic estimates the probability that a given dataset has been drawn from a random uniform distribution (null hypothesis).
- **Visual methods.** The Visual Assessment of cluster tendency -VAT- algorithm (Bezdek and Hathaway, 2002) computes the dissimilarity matrix between the observations in the dataset, and rearranges it so that similar objects are close to one another; its output is the ordered dissimilarity image (ODI). Typically, one computes the ODI of both the real dataset and a random dataset generated from it, so that the results can be compared.

Hierarchical clustering

As its name would suggest, hierarchical clustering is a clustering technique intended to build a hierarchy of clusters of the observations in a dataset (James et al., 2013). Its main advantages are (i) that it results in a dendrogram -an intuitive tree-based representation of the observations-; and (ii) that it is not necessary to specify the number of clusters in advance, as the dendrogram covers all possibilities from the lowest level, at which each cluster contains a single observation, to the highest one, at which all the observations belong to the same cluster.

Consequently, hierarchical clustering is extremely useful to conduct analysis at different levels of resolution, which is precisely the reason why we chose it to explore the different subsistence economies. Nevertheless, it is noteworthy that not committing to a number of clusters beforehand can also be regarded as a drawback, namely the lack of an objective criterion to determine the number of clusters, which can result in the biases of the analyst influencing the choice.

Determination of the optimal number of clusters

Once the data have proven to be clusterable and the clustering algorithm has been selected, the next step is trying to ascertain the optimal number of clusters. However, there is no one answer to this question, as the optimal number of clusters depends on both the partitioning algorithm chosen and the similarity/dissimilarity metric used. In fact, there exists a great variety of indices and methods conceived to determine the optimal number of clusters, see, for instance, the elbow method (Kassambara, 2015) -which selects the number of clusters that minimises the total intra-cluster variation-, the average silhouette method (Kaufman and Rousseeuw, 1990) -which maximizes the quality of clustering, i.e., how well each observation lies within its cluster-, the gap statistic (Tibshirani et al., 2001) -which chooses the clustering furthest away from the random uniform distribution of points-, all the indices included in the NbClust R package (Charrad et al., 2014), and consensus clustering approaches (Monti et al., 2003). For further details on the NbClust R package, please refer to its reference manual available at (Charrad et al., 2015). As regards consensus clustering, it is a resampling-based method designed to determine the consensus number of clusters in the data, and to assess and represent cluster stability. In particular, consensus clustering takes the original dataset, creates a given number of perturbed datasets via the resampling technique of choice, applies the clustering algorithm selected to those perturbed datasets, and finally assesses the agreement among the multiple runs. Its underlying assumption is that the more robust clusters are to sampling variability, the more likely it is that they reflect the real structure of the data.

In the present work, we opted for computing all the above-mentioned metrics and selecting the best number of clusters either in accordance with the majority rule, with consensus clustering and/or with both.

Cluster entropy

After choosing the number of clusters, in the present contribution we have drawn on the concept of information entropy to formally define mixed economies. Within the framework of information theory, the entropy of a random variable is defined as the uncertainty intrinsic in the variable’s possible outcomes (Shannon, 1948). Formally, the entropy of a discrete random variable X is calculated as follows:

$$H(X) = -\sum_{i=1}^{n} P(x_i) \log_b P(x_i) \qquad \textbf{(25)}$$

Where $X = \{x_1, \cdots, x_n\}$, i.e., $x_1, \cdots, x_n$ are the possible outcomes of X, and they occur with probability $P(x_1), \cdots, P(x_n)$. Note that the entropy is maximal when all possible outcomes are equiprobable (uniform probability distribution).

In the context of the present contribution, a subsistence economy is defined by five different variables, namely the percentages of dependence on gathering, hunting, fishing, husbandry and agriculture, which are interpreted as the probability of relying on those food sources. Therefore, given that the maximal entropy is attained when all possible outcomes follow a uniform distribution, the subsistence economies with the same percentage of dependence on the five alternatives will be the ones with maximal entropy. Consequently, mixed economies can be formally defined as those subsistence combinations with high/the highest information entropy.

SUPERVISED LEARNING APPROACH

Supervised learning techniques are intended for the type of problems in which each observation -codified as a vector with the corresponding values for the different predictor variables- has an associated response measurement. In particular, supervised learning methods seek to fit a model that relates the response to the predictors, either for prediction purposes or to better understand the relationships between the response and the predictors (James et al., 2013).

Supervised learning problems can be, in turn, divided into two main categories based on their response variable: regression problems -quantitative response- and classification problems -qualitative response-; specific machine learning techniques have been developed for each problem typology, existing also methods that can be used for both quantitative and qualitative responses.

As regards the present contribution, once structure has been found in the data, and the prevailing subsistence economies have been identified via clustering -i.e., the number of clusters has been selected and hence each observation has been assigned to a cluster-, we can use such information as the response variable to conduct supervised learning analyses. More precisely, we have opted for supervised learning approaches to address our second research question, i.e., *to assess the role played by ecological settings in the configuration of the different subsistence economies*.

First, it is necessary to clarify that this second stage of the analyses has been conducted on what we called the supervised learning database: a dataset including all the variables in Table 12 except for the percentages of dependence on the different subsistence strategies -variables from EA001 to EA005-, plus the response variable, namely the cluster to which each observation belongs; note that we have chosen the response variable for k = 15, which is the highest level of resolution. Therefore, given that our response variable is qualitative, we are facing a classification problem. Notably, we did not include variables from EA001 to EA005 in the supervised learning database because the clustering analysis has been conducted exclusively on the five of them, and thus they are closely related to the response variable, which could hinder the identification of other possible relationships between the rest of socioecological variables and the clusters found.

When joining the variables in Table 12 to configure the supervised learning database, we found that we had missing data, i.e., that certain societies in the EA had no information available for some of the variables coming from other data sources. To solve this problem, instead of dropping those societies with missing values, we kept all of them and applied a multiple imputation technique (as opposed to single imputation) to estimate the statistical uncertainty attributable to the missing data. This approach consists in creating multiple complete datasets by independently imputing the missing data via stochastic draws from the distributions of the observed data. In particular, in our work we have used the Multiple Imputation by Chained Equations (MICE) method (van Buuren, 2007), which is implemented in the *mice* R package (Buuren and Groothuis-Oudshoorn, 2011a). MICE assumes that data are missing at random (MAR) -i.e., that the probability that a value is missing depends only on the observed data-, and consists in iteratively estimating the conditional distributions of each variable from the rest of the variables. To increase stability, the imputation process of all variables is repeated through cycles. In our analysis, we have generated 100 different datasets, being each one of them the result of 50 cycles. As for the MICE imputation method chosen, we have used a recursive partitioning approach: random forests (Doove et al., 2014; Shah et al., 2014), so as to take into account possible nonlinearities, interactions and both numerical and categorical data. Recall that even though variables from EA001 to EA005 have not been considered for the supervised learning analyses, we did include them in the database on which multiple imputation was conducted, so as to help get more accurate estimates of the missing values.

Regarding the supervised learning model to be fitted to our data, from all techniques suited for classification problems, we have chosen random forest (Breiman, 2001); the rationale behind this choice is to be found in four main reasons: (i) as previously stated, random forest can handle both numerical and categorical predictors; (ii) it is an ensemble method, which translates into the resulting model having a good bias-variance trade-off -i.e., the resulting model is neither too general nor overfitting the data- (Hastie et al., 2009; James et al., 2013); (iii) in an exhaustive evaluation of up to 179 classifiers, random forest was found to be the best family of classifiers (Fernández-Delgado et al., 2014); and (iii) it allows to conduct both individual and group variable importance analyses. Nevertheless, to be sure that our choice was appropriate, we have compared random forest with several benchmark and highly performant classification algorithms. More specifically, we have conducted an ANOVA test and the Duncan’s New Multiple Range Test (Duncan, 1955) on the accuracies obtained by stratified 10-fold cross-validation with the following classifiers: ZeroR (Frank et al., 2016), OneR (Holte, 1993), AdaBoost (Schapire, 2013), Support Vector Machine with polynomial kernel (Cortes and Vapnik, 1995; James et al., 2007), rotation forest (Rodriguez et al., 2006) and random forest (Breiman, 2001). Note that in the Duncan’s New Multiple Range Test, if two classifiers belong to the same group, no statistically significant differences exist between them, which implies that the choice of the classifier can be based on criteria other than accuracy -see for instance interpretability, model simplicity, etc.-.

As far as variable importance analyses are concerned, their raison d’être is that predictors are seldom equally important in supervised learning models; in fact, usually only a subset of them is relevant to determine the response. Therefore, it is of interest to quantify the relative contribution of each variable (individual variable importance analysis) or group of variables (group variable importance analysis) in predicting the response. In particular, variable importance is calculated as the mean decrease in accuracy after randomly permuting a given predictor (Breiman, 2001) or a group of predictors (Gregorutti et al., 2015). Recall that the more the accuracy is reduced after the permutation, the more important the predictor/group of predictors.

Remarkably, variable importance analyses become even more important in the context of ensemble models, since ensembles result into better accuracy than single-tree models, but they do so at the expense of interpretability.

RESULTS

EXPLORATORY DATA ANALYSIS BY MEANS OF UNSUPERVISED LEARNING TECHNIQUES

PCA

The results of the PCA conducted on the subsistence dataset -variables from EA001 to EA005- can be found in Table 13, where we can see that the total variance of the data is effectively explained by the first four PCA dimensions.

Table 13. Results from PCA on the subsistence dataset. The first four dimensions explain all the variance in the data.

PC Dim.	1	2	3	4	5
Eigenvalues	2.624	1.043	0.842	0.492	0.000
% of var.	52.477	20.851	16.841	9.831	0.000
Cumulative % of var.	52.477	73.328	90.169	100.000	100.000

In Fig. 12 we can see how the different variables considered -percentage of dependence on gathering, hunting, fishing, husbandry and agriculture- correlate with the first four PCA dimensions. The actual correlation values and their respective *p*-values can be found in Table S 1 from the Supplementary Material.

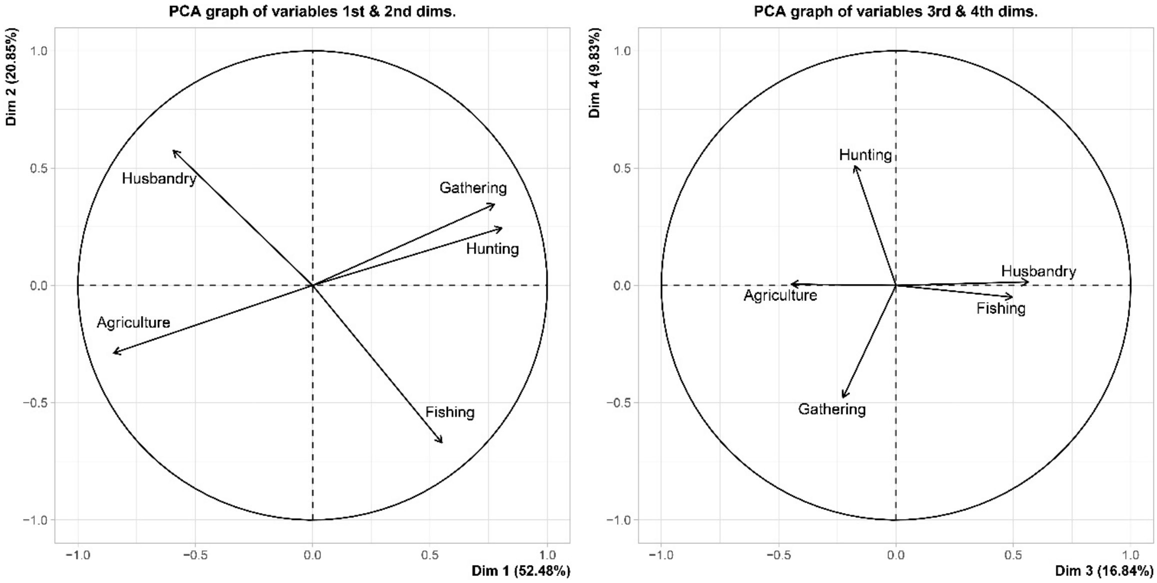

Fig. 12. PCA graph of variables for dimensions 1:2 and 3:4 respectively.

A contextualised interpretation of these four PCA dimensions may be summarised as follows:

- Dimension 1 explains 52,48% of the variance. In overall terms, it corresponds to the traditional opposition between hunting-gathering and agriculture. The immediate interpretation of such result is that at least for our EA sample, the traditional dichotomic view of subsistence economies explains only half of the picture.
- Dimension 2 explains 20,85% of the variance. Once each society has positioned itself to one side or the other of the previous hunting-gathering vs. agriculture divide, dimension 2 presents an additional disjunctive, in this case between animal husbandry and fishing. Therefore, the interpretation thus far would be that -in general terms- agriculturalists do not hunt or gather, and that if you fish you do not practise animal husbandry -and vice versa-. In addition, it is important to note that in accordance with the relative position of husbandry and fishing in the PCA graph of variables for dimensions 1:2, husbandry generally accompanies agriculture, while fishing is most frequently found complementing hunting-gathering economies.
- Dimension 3 explains 16,84% of the variance. This third dimension presents an opposition between agriculture and husbandry & fishing. A plausible reading of its meaning would be that once a society is profiled in accordance with the two previous disjunctives, dimension 3 informs about the intensification choice, i.e., if they intensify agriculture (plant resources) or husbandry/fishing (animal resources).
- Dimension 4 explains 9,83% of the variance. The divide it presents is between gathering and hunting, and hence it may be understood as follows: for those societies who positioned themselves as hunter-gatherers in the previous dimensions, dimension 4 captures if they intensify gathering or hunting.

ASSESSMENT OF CLUSTERING TENDENCY

- **Statistical methods: Hopkins statistic (*H*).** As previously stated, Hopkins statistic tests the spatial randomness of the data. An *H* value close to 0.5 is in perfect agreement with the null hypothesis that the dataset was generated by a uniform distribution. On the other hand, an *H* value close to zero means that the data are highly clusterable -the null hypothesis can be rejected-. Our subsistence dataset has an *H* value of 0.1527 (significantly below the threshold of 0.5), which means that our data are highly clusterable.
- **Visual methods. The Visual Assessment of cluster tendency -VAT- algorithm.** In Fig. 13 we can see the ODIs obtained for both the subsistence dataset and a random dataset generated from it, using the Euclidean distance as dissimilarity metric. From the comparison of the two, it becomes clear that our subsistence dataset presents a clear structure and that it is therefore significantly different from the random one.

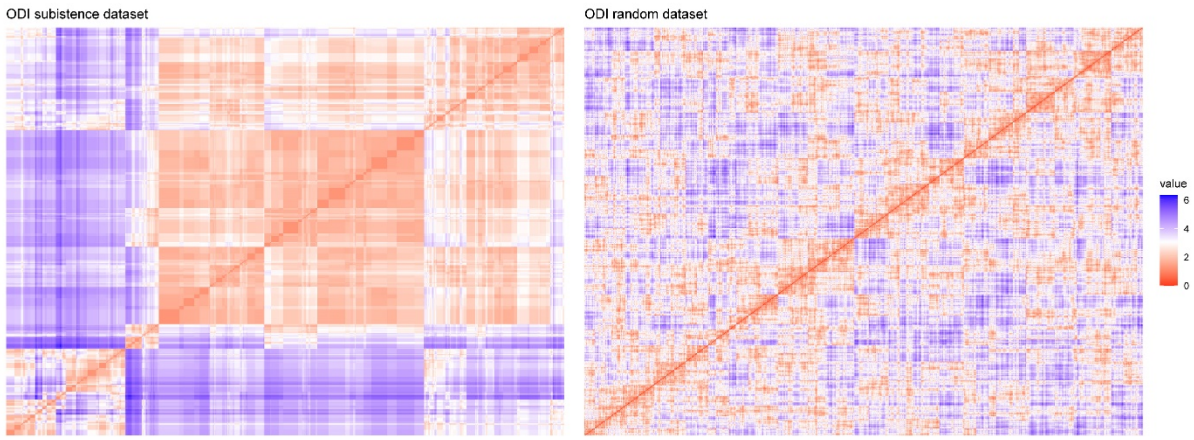

Fig. 13. ODIs of the subsistence dataset (on the left) and a random dataset generated from it (on the right). Note that according to the legend colour red means high similarity (low dissimilarity) and blue high dissimilarity. After comparison with the random dataset, it becomes clear that our subsistence data have structure.

HIERARCHICAL CLUSTERING

Having shown in the previous section that the data are clusterable, here we proceed to explain the hierarchical clustering implementation that we applied to our subsistence dataset. We have worked with the R package *factoextra* (Kassambara and Mundt, 2020), and more precisely, we have used the the *eclust* function selecting the Euclidean distance as dissimilarity metric, and Ward's method as the agglomerative method.

DETERMINATION OF THE OPTIMAL NUMBER OF CLUSTERS

As emphasised in the Methods section, one of the main strengths of hierarchical clustering - and the reason why we chose it- is that it enables to conduct analyses at different scales of resolution. Accordingly, in the present contribution we have decided to explore the resulting dendrogram at three levels: k = 2, 7 and 15. The reasons justifying these choices may be summarised as follows:

- ***k* = 2** was chosen since it is the optimal number of clusters proposed by NbClust following the majority rule, and it is also the optimal value according to elbow method and average silhouette method; additionally, the consensus matrix for k = 2 happens to be extremely clean, which is an indicator of good clustering. For the details of the values obtained for the different indices please refer Table S 2 and Table S 3 in the Supplementary Material. As regards the consensus matrices obtained with consensus clustering, for a visual inspection of them please refer to the folder *Consensus matrices & CDF* available at the GitHub repository of our paper: https://github.com/Virahe/Lets-go-Fishing. Note that in such visual representation, each consensus matrix has been arranged so that items belonging to the same cluster are adjacent to each other; consequently, perfect consensus corresponds to a diagonal matrix with non-overlapping blocks along the diagonal.
- ***k* = 7** and ***k* = 15** were chosen after the joint analysis of the consensus matrices, the evolution of the cumulative distribution functions (CDF's) as k increases, and the increase in the area under the CDF for the different k's. Recall that bimodality in the CDF is considered as a signal of cluster structure, and that if $k < k_{TRUE}$ the area under the CDF increases with k, but once k_{TRUE} is reached, any further increase in k does not translate into a significant increase in the area under the CDF. Taking into account all the above, we assessed the evolution of the CDF's and of the delta function -both showed in Figure S 1 from the S1 Appendix in the Supplementary Material-, and found that there are two distinct levels worth exploring: (i) the one ranging from k = 5 to k = 10, and (ii) that ranging from k = 11 up to k = 20. Both levels have been analysed at the intermediate value of the intervals, i.e., k = 7 and k = 15 respectively. For further details on the choice of k = 7 and k = 15 please refer to S1 Appendix in the Supplementary Material.

DETAIL OF THE CLUSTERS OBTAINED FOR *K* = 2, 7 AND 15

In the present section we succinctly interpret the clusters obtained at the three levels selected Fig. 14 is a sunburst diagram that summarises the cluster precedence relationships. Note that the lowest level of detail, i.e., k = 2, is to be found in the inner circle, and that the greatest detail –k = 15– is presented in the outermost circle. Recall as well that the percentage values accompanying the cluster descriptions are the mean values obtained for the given variable across all societies in that cluster.

At the lowest level of resolution, we find the traditional dichotomy between hunting-gathering-fishing and agropastoralism. When moving to the intermediate level, the differences between the distinct subsistence alternatives become more evident: the hunter-gatherer-fisher (HGF) group is divided into three depending on which of the three activities is more heavily relied upon: (1) gathering, (2) hunting or (3) fishing; as for the agropastoralist group, it is splitted into four clusters: (4) the strictly pastoralists, whose strategy is based predominantly on animal husbandry and complement it with a low percentage of agriculture; (5) the agropastoralists, who are strongly dependent on agriculture and complement their subsistence economy with animal husbandry; (6) the group which we have agreed to name *agrofishers* since their subsistence economy is a mix of fishing and agriculture, being the rest of possible activities -hunting, gathering and husbandry- underrepresented; and (7) those with what we have called the *Whole Spectra Economy* (WSE), i.e., whose subsistence economy encompasses hunting, gathering and fishing at approximately par value, and a great percentage of agriculture.

Eventually, at the highest level of resolution we identify the more subtle nuances according to which the previous seven clusters are further subdivided. As for the three HGF clusters, they are partitioned into six clusters for k = 15: the HGF's more dependent on gathering are divided into two clusters: (1.A.) those who are just hunter-gatherers (HG's) more reliant on gathering –we claim that they are simply HG's since fishing represents a negligible value in this cluster–; and (1.B.) the archetypal HGF's with a similar percentage of dependence on each of the three sources; the group of HGF's more heavily reliant on hunting is maintained and now named (2.BIS.); as regards the cluster of HGF's more heavily reliant on fishing, they are splitted into three clusters: (3.A.) the eminently fishers, with a percentage of dependence on fishing greater than 70%; (3.B.) hunter-fisher groups with similar percentages of dependence on each of the two strategies and a negligible level of gathering; and (3.C.) HGF's – Fishers, who in spite of being more heavily dependent on fishing resources, present significant percentages -greater than 20%- of gathering and hunting. Concerning the other four clusters -the ones with a given dependence on agriculture-, for k = 15 they have been further splitted as follows: the pastoralist cluster has been divided into two different groups: (4.A.) the outstandingly pastoralists, which in this smaller cluster present average values of up to a 75% dependence on animal husbandry and just a 13% complementation with agriculture; and (4.B.) agropastoralists that are more strongly dependent on animal husbandry than in any other source -up to 49% on average-, and that complement their strategy not only with agriculture (22%) but also with hunting (12%) and fishing (11%), what allows to consider them as having a mixed economy. Regarding the agropastoralist cluster, it has been divided into three clusters: (5.A.) the strictly agropastoralists -again- whose percentages of dependence on both agriculture and husbandry are almost maintained with respect to its homonymous cluster at k = 7; (5.B.) a second group of agropastoralists more heavily reliant on animal husbandry; and (5.C.) what we have called *agrohunting*, which is still heavily reliant on agriculture, but instead of complementing the subsistence economy with just husbandry, it also presents a significant degree of hunting -in fact, the percentage of dependence on hunting is greater than that of husbandry-. As for the *agrofishing* cluster, it has been partitioned into two clusters in accordance with the percentages of dependence on agriculture, fishing and husbandry: (6.A.) *agrofishers* with an average 47% reliance on agriculture, almost 40% dependence on fishing and a marginal contribution of husbandry to the diet of up to 7%; and (6.B.) *agrofishers* more strongly dependent on agriculture (54%), with a 20% percentage of dependence on fishing, and a greater weight of husbandry (13%). Lastly, the cluster of the WSE has been splitted into two: (7.A.) the truly *agrohunters*, which exhibit an average 45% reliance on agriculture, 28% on hunting and complement their strategy with an 18% of fishing; and (7.B.) the strictly WSE, which is not significantly altered with respect to its homonymous cluster at k = 7, presenting now an average reliance on agriculture of up to 35% and of 21% on hunting, 25% on gathering and 15% on fishing.

At this point, it would be interesting to recall that even though for k = 2 there is no trace of mixed economies, and at k = 7 they are restricted to two clusters –agrofishers and the WSE–, when we increase the level of detail and work at a fine-grained scale -k = 15-, they make up a significant percentage of the possible subsistence economies, in fact, 5 out of 15 clusters can be considered as mixed –clusters (4.B.), (6.A.), (6.B.), (7.A.) and (7.B.) –. For further details on this aspect please refer to the discussion, where it is examined in depth.

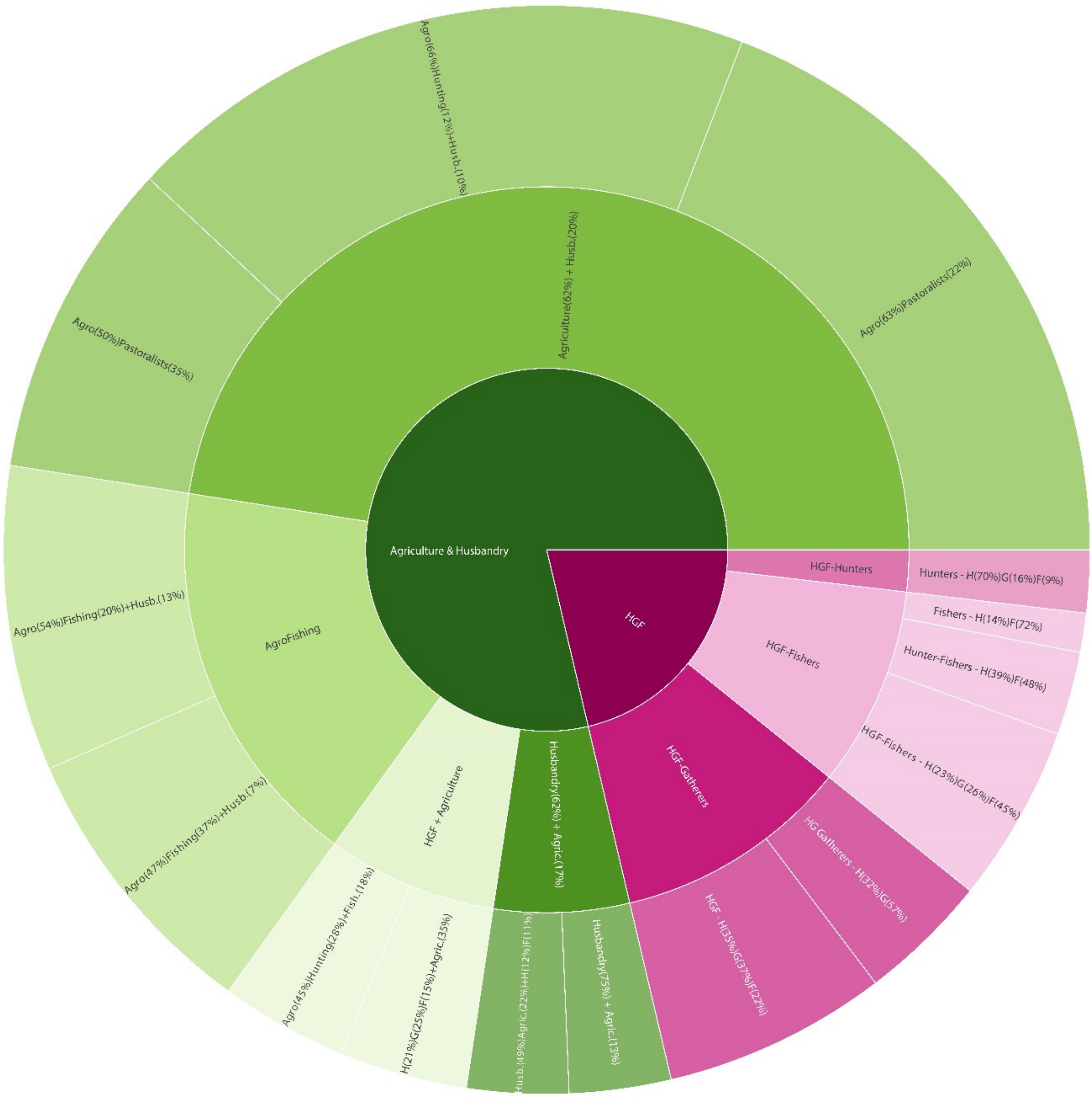

Fig. 14. Sunburst of the different subsistence strategies identified via hierarchical clustering for *k* = 2, 7, 15. A short description is provided for each of the clusters. Note that the size of the circular sectors is proportional to the number of societies falling under each cluster.

Additionally, we decided that it could be of interest to represent the different clusters in a map with the terrestrial ecoregions of the world proposed by Olson et al. (2001). Therefore, we created Fig. 15 and Fig. 16. In Fig. 15 we can see all societies considered in the present study placed in accordance with their latitude and longitude and coloured according to the cluster they belong to for $k = 7$; note that the map has intentionally been coloured to represent the different biomes, and that a legend with the average percentages of the different variables for each cluster has been provided. As for Fig. 16, it is the replication of Fig. 15 for $k = 15$, with the caveat that instead of representing the 15 clusters, as the interest of the present paper is on the agricultural transition and the middle ground, we have just represented the 9 clusters with a given level of dependence on agriculture and/or husbandry.

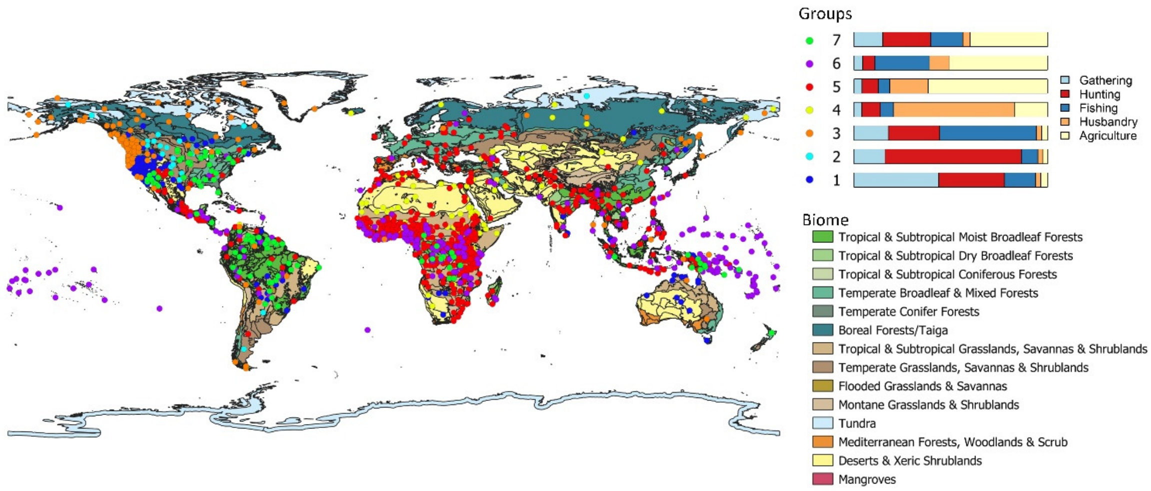

Fig. 15. Map with the subsistence clusters obtained for *k* = 7. The different societies have been placed in accordance with their latitude and longitude and coloured according to the cluster they belong to. The different world regions have been coloured to represent the different biomes. Two legends provided: the upper right one presents the detail of the average percentages of dependence on gathering, hunting, fishing, husbandry and agriculture of each of the clusters. The lower right one is the legend of the biomes. Map source - (Olson et al., 2001).

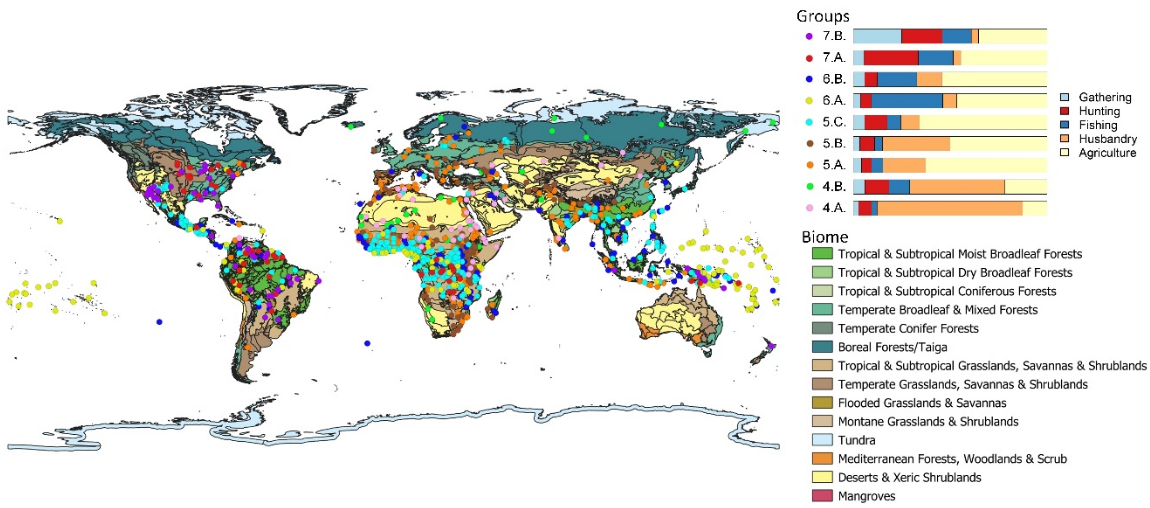

Fig. 16. Map with 9 of the subsistence clusters obtained for *k* = 15. The different societies are placed in accordance with their latitude and longitude and coloured according to the cluster they belong to. Only those subsistence strategies with a significant level of agriculture and/or husbandry have been considered. Two legends provided: the upper right one presents the detail of the average percentages of dependence on gathering, hunting, fishing, husbandry and agriculture of each of the clusters. The lower right one is the legend of the biomes. Map source - (Olson et al., 2001).

CLUSTER ENTROPY

As stated in the Methods section, in this work we have formally defined mixed economies as those subsistence strategies with high/the highest information entropy -remember that maximal entropy is achieved when all possible outcomes follow a uniform distribution, which in our case would translate into subsistence economies with the same percentage of reliance on the five variables considered (gathering, hunting, fishing, husbandry and agriculture)-. Note that in our results, the WSE is the subsistence economy closest to the case with theoretical maximal entropy.

To illustrate the concept, we have calculated both the entropy of each society's subsistence strategy and the entropy of each cluster's average strategy for *k* = 2, 7 and 15. (Recall that a cluster's average strategy is calculated by averaging the percentages of dependence on gathering, hunting, fishing, husbandry and agriculture across all societies in the cluster). For each level of analysis, we have obtained: (i) a summary table with the clusters' average strategies, their entropy, their standard deviation, two columns quantifying the number of variables with a percentage of dependence equal or greater than 15% and 10% respectively, and a concise interpretation of each cluster; as well as (ii) a figure with the entropy distributions of all the clusters in that resolution level. For simplicity, here we just present the results obtained for *k* = 7, which are provided in Table 14 and Fig. 17 respectively. Nevertheless, the detail of the entropy results obtained for the other two levels of resolution can be found in the Supplementary Material, Table S 4 and Figure S 2 for *k* = 2 and Table S 5 and Figure S 3 for *k* = 15.

Table 14. Summary table for k = 7. It includes cluster number, each cluster's average strategy, -the average of the percentages of dependence on gathering, hunting, fishing, husbandry and agriculture across all societies in the cluster-, their entropy, standard deviation, the number of variables with a percentage of dependence equal or greater than 15% and 10%, and a succinct interpretation of the cluster. Note that the table has been sorted in ascending order of entropy.

	Clusters' average strategies (Mean values per variable and cluster)

Cluster nb	Gathering (%)	Hunting (%)	Fishing (%)	Husbandry (%)	Agriculture (%)	Entropy	SD	Limit 15	Limit 10	Interpretation
2	16,40	69,82	8,50	2,64	2,64	0,95	28,42	2	2	HGF - Hunters
5	4,74	8,21	5,91	19,67	61,47	1,14	23,93	2	2	Agriculture(62%) + Husb.(20%)
4	4,43	9,51	6,77	61,89	17,40	1,15	23,92	2	2	Husbandry(62%) + Agric.(17%)
3	18,16	26,36	49,42	2,73	3,33	1,22	19,27	3	3	HGF - Fishers
1	44,00	33,64	16,00	2,64	3,73	1,24	18,33	3	3	HGF - Gatherers
6	4,77	6,16	28,20	10,30	50,57	1,25	19,49	2	3	AgroFishing
7	15,21	24,55	16,46	3,80	39,99	1,42	13,40	4	4	WSE: HGF + Agriculture

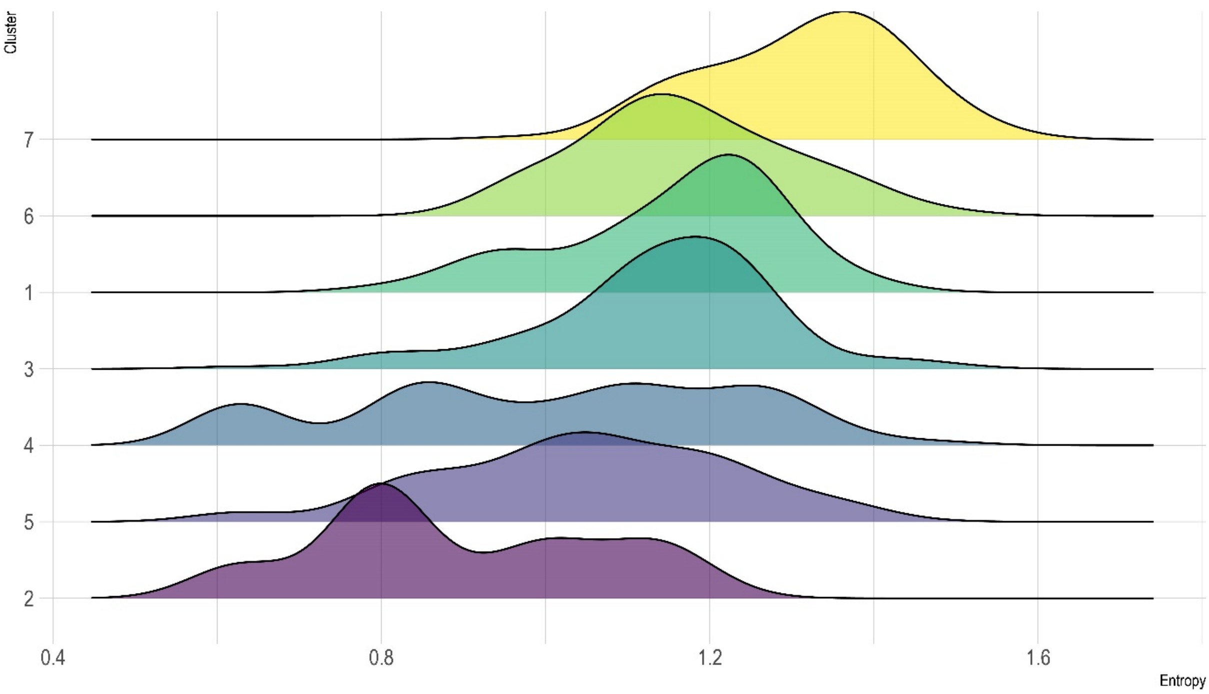

Fig. 17. Ridgeline plot of the entropy distributions of each cluster for *k* = 7. Recall that the distributions have been sorted in ascending order of entropy along the vertical axis.

SUPERVISED LEARNING APPROACH

COMPARISON OF DIFFERENT BENCHMARK AND HIGHLY PERFORMANT CLASSIFICATION ALGORITHMS

As stated in the Methods section, we have compared random forest (our intended algorithm of choice) with several benchmark and high-performance classification algorithms on our supervised learning database; the scale of resolution selected has been $k = 15$, since it is at this level that the diversity of the middle ground strategies becomes more evident. Note that since the supervised learning database had missing data, and hence we obtained 100 imputed datasets via the MICE multiple imputation method, the comparison of the algorithms has been conducted on the 100 imputed datasets.

As we explained, the classifiers selected were the following: ZeroR, OneR, AdaBoost, Support Vector Machine (SVM) with polynomial kernel, rotation forest and random forest. ZeroR and OneR are rule-based classifiers typically used to establish the baseline performance, as ZeroR trivially predicts the most frequent class, while OneR creates one rule for each of the predictors in the dataset and establishes as its 'one rule' the one with the smallest classification error. The rest of the classifiers chosen are high-performant classifiers (Fernández-Delgado et al., 2014; Bagnall et al., 2018). Our experiments have been conducted in Weka (Frank et al., 2016); stratified 10-fold nested cross-validation was used for parameter tuning in AdaBoost and the SVM with polynomial kernel -for the details of the parametrizations explored please refer to our GitHub repository: https://github.com/Virahe/Lets-go-Fishing-; as regards rotation forest and random forest, in accordance to (Bagnall et al., 2018) tuning makes no significant improvement to them as long as reasonable parameter values are set; therefore, given that parameter tuning is extremely time-consuming, we used the parametrization they propose in TABLE II and evaluated the two algorithms by means of simple stratified 10-fold cross-validation.

To assess if statistically significant differences existed between the six classifiers on our data, we conducted one-way ANOVA tests on the 10-fold cross-validation accuracies obtained for the six of them on each imputed dataset. In all the 100 cases the null hypothesis of equality of means could be rejected. Thereupon, having proved that statistically significant differences existed between the algorithms, we conducted the Duncan's New Multiple Range Test -again on the results for the 100 datasets- to get the detail of the differences. In all the 100 cases, random forest belonged to group "a", the group with the highest performance. In 99 out of 100 datasets group "a" was composed by random forest, rotation forest and the SVM with polynomial kernel. In the remaining dataset, random forest belonged to group "a", rotation forest to group "ab", and the SVM with polynomial kernel to group "b" –recall that classifiers with the same letter are not statistiscally significantly different–. Hence, we can conclude that since random forest belongs to the group with the highest performance in 100 out of 100 of the datasets, it is perfectly valid to justify its choice on grounds of the variable importance analyses it enables to conduct.

VARIABLE IMPORTANCE ANALYSES

As we have already discussed, since random forest is not straightforwardly interpretable, it is of interest to conduct variable importance analyses to assess the relevance of a given variable or a group of variables in predicting the response. In coherence with the previous section, variable importance analyses have been conducted for k = 15.

INDIVIDUAL VARIABLE IMPORTANCE ANALYSIS

We have conducted individual variable importance analysis on the 100 imputed datasets. The results provided in Fig. 18 show the importance of each variable averaged across the 100 datasets. Remember that we have conducted individual variable importance analysis in accordance to Breiman (2001), and that therefore, the importance of each variable is the percent increase in misclassification rate obtained after randomly permuting the values for that variable.

GROUP VARIABLE IMPORTANCE ANALYSIS

Group variable importance analysis is intended to assess the impact of an aggregated set of variables in the resulting predictive accuracy of the random forest algorithm. In the present contribution, four groups of variables have been considered. Please find below the detail of the variables that constitute each group.

Group 1 - Agriculture-related variables:

- EA028 – Agriculture intensity.
- EA029 – Major crop type.
- EA039 – Plow cultivation.

Group 2 - Husbandry-related variables:

- EA040 – Domestic animals’ type.
- EA041 – Milking.

Group 3 – Demographic/degree of complexity variables:

- EA030 – Prevailing type of settlement pattern.
- EA033 – Political complexity.
- EA202 – Population size.

Group 4 – Ecological variables:

- Variables from Jenkins et al. (2013):
    - Amphibian richness.
    - Bird richness.

  - Mammal richness.

- Variables from Kreft and Jetz (2007):
  - Vascular plants richness.
- Variables from Moderate Resolution Imaging Spectroradiometer (NASA. Net Primary Productivity (1 month - TERRA/MODIS)):
  - Annual Net Primary Production Variance.
  - Monthly Mean Net Primary Production.
  - Net Primary Production Constancy.
  - Net Primary Production Contingency.
  - Net Primary Production Predictability.
- Variables from Terrestrial Ecoregions of the World (Olson et al., 2001):
  - Biome.
- Variables from Baseline Historical (1900-1949), CCSM ecoClimate model (Lima-Ribeiro, 2015):
  - Annual Mean Temperature.
  - Annual Precipitation Variance.
  - Annual Temperature Variance.
  - Monthly Mean Precipitation
  - Precipitation Constancy.
  - Precipitation Contingency.
  - Precipitation Predictability.
  - Temperature Constancy.
  - Temperature Contingency.
  - Temperature Predictability.

The results of our group variable importance analyses averaged across the 100 imputed datasets can be found in Fig. 19.

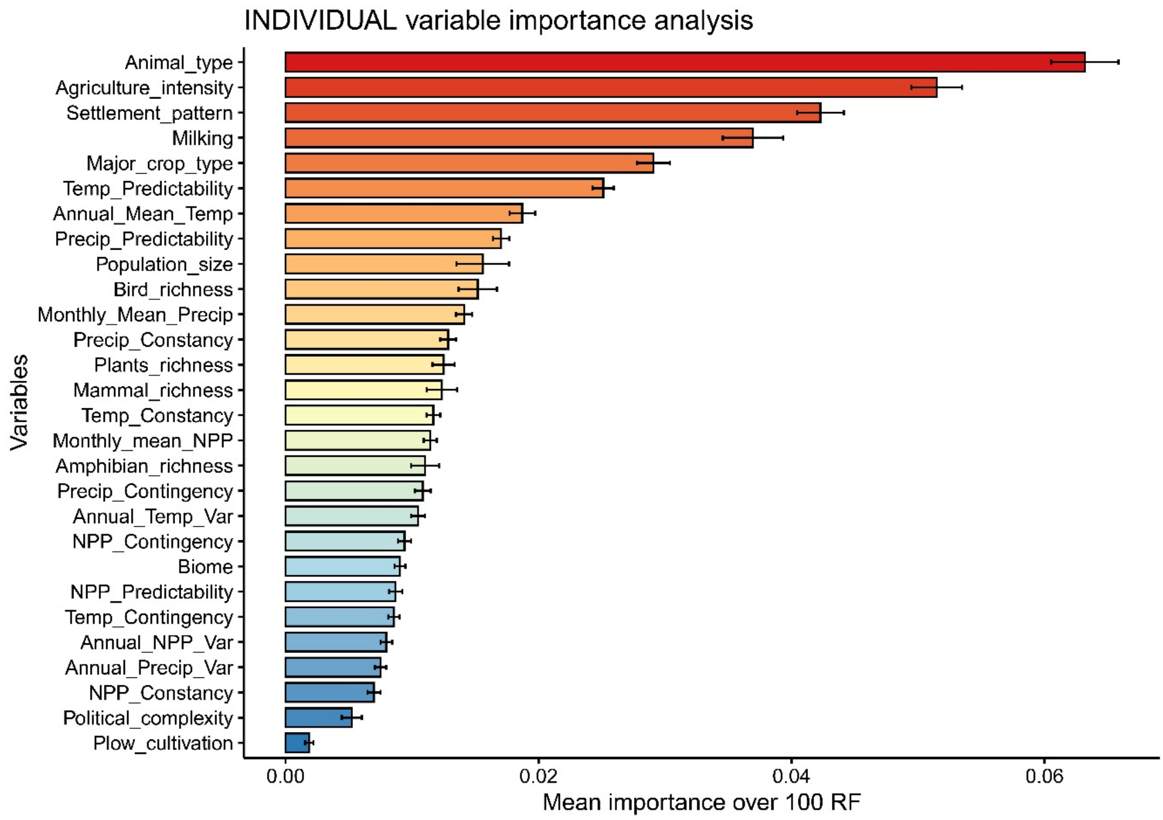

Fig. 18. Breiman's individual variable importance averaged across the 100 imputed datasets. One standard deviation error bar.

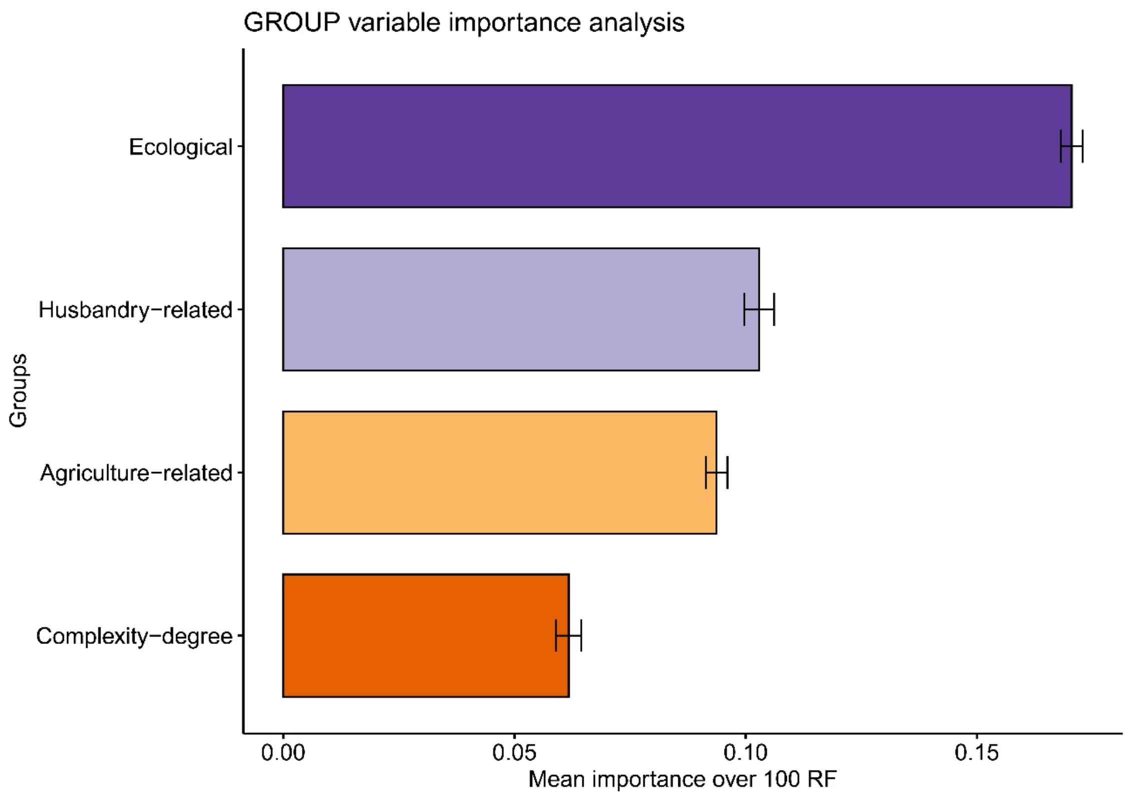

Fig. 19. Group variable importance averaged across the 100 imputed datasets. One standard deviation error bar.

DISCUSSION

In spite that standardised databases for the Digital Humanities in general, and all those available at D-PLACE (Kirby et al., 2016) in particular, are not exhaustive, they are representative enough of human societies' variability and allow to identify previously uncharted regions, hence being particularly suitable for cross-cultural studies such as the present one. Nevertheless, it is also noteworthy that since the contents in these databases are commonly quite generalist, one should be extremely careful when extrapolating conclusions to specific cases.

That said, we proceed to revise our three research questions in the light of the results obtained.

QUESTION 1: REGARDING SUBSISTENCE STRATEGIES, ARE ALL COMBINATIONS VIABLE OR DO SPECIFIC PATTERNS EXIST?

This question has been specifically addressed by means of the unsupervised learning approach; the answer we found is that clear patterns exist in the data, hence not being all combinations viable. More specifically, the PCA analysis has allowed us to identify the four main axes of variability in the subsistence database, which explain up to 100% of the variance, and the data have proved to be highly clusterable.

As regards PCA analysis, remarkably, the first PCA dimension -which explains up to 52.48% of the variability- correlates quite clearly with the traditional dichotomy between hunting-gathering and agropastoralism. Thereupon, we can assert that at least for our particular EA sample of 1290 societies, the binary conceptualisation has proved to be both useful and insufficient. It is indeed useful as it explains approximately half of the variance in our data, but it is at the same time insufficient as it leaves an equally important half unexplored. Assuming that our sample may be in fact representative enough of the entire phenomenon, this finding could suggest that because of embracing the traditional dichotomic approach, half of the picture could have been disregarded.

Additional PCA-derived highlights would be -as noted in the results section- (i) the exclusive relationship found between fishing and animal husbandry in dimension 2, which corresponds to the fact that societies with a high reliance on fishing generally do not have the need to breed livestock and vice versa -i.e., pastoralists are mostly found in arid areas with no access to fishing resources-; and (ii) the disjunctive from dimension 3 between agriculture and husbandry-fishing, which is clearly related to intensification strategies, namely, if it is decided to intensify on plant resources or on animal protein.

Regarding cluster analysis, the fact that the subsistence dataset is significantly different from a random distribution and highly clusterable implies that recurrent specific subsistence combinations exist. As stated in the methods section, we opted for hierarchical clustering because it allows to explore the problem under consideration at different scales. More precisely, the three levels of granularity selected (k = 2, 7, 15) could be regarded as corresponding to the macro-scale, the mesoscale and a more detailed scale respectively.

The macro-scale -which provides a general overview of the phenomenon- finds again the traditional division between HGF and agropastoralists; this fact complements and reinforces the reading that we made in the context of the percentage of variance explained by the first PCA dimension: that the classic binary conceptualisation corresponds to a broad-brush approach, hence being quite oversimplistic and incomplete. For this reason, here we will focus primarily on the mesoscale, since it is detailed enough to distinguish the different subsistence strategies, while being at the same time general enough so as to get a global view of the matter. Nevertheless, when of interest, we will also delve into the specifics of certain strategies at the greatest level of detail, i.e., for k = 15.

CLUSTER INTERPRETATION FOR K = 7

Recall that in the present section, in addition to exploring the economic structure of each of the clusters found, we will also provide some insights in relation to the biomes where they appear. For the details on geographical location and entropy values, unless otherwise specified, please refer Fig. 15 and Table 14 respectively.

HGF STRATEGIES

- **Cluster 1 (136/1290 societies): HGF – Gatherers – H(34%)G(44%)F(16%)**

  This cluster corresponds to a gathering-hunting economy in which wild plant management constitutes the most relevant activity. Societies belonging to cluster 1 are predominantly located in areas with deserts and xeric shrublands biome (Australia, South Africa, NW coast of the North American continent), existing also some cases in the biomes tropical and subtropical grasslands, savannas and shrublands, and boreal forests.

  The prevalence of gathering in arid areas -which may seem counterintuitive- has its rationale in the fact that plants collect water, being hence an extremely valuable resource for water obtention in those environments. Examples of the implementation of these techniques can be found in the literature for Australia -where aboriginal communities extract water from the trunk of the cajuput-tree (Clarke, 2011)- and the Kalahari desert -where melons constitute and important source of moisture (Knight, 1995)-. The existence of such arid-areas-management dynamics has been considered in Archaeology -and is still being explored- as an explanation for the human habitation of desertic environments (Wills, 1988; Nabhan et al., 2020).

- **Cluster 2 (24/1290 societies): HGF – Hunters – H(70%)G(16%)F(9%)**

  Cluster 2 corresponds to a hunting economy that is marginally complemented with plant gathering and fishing. It tends to appear in northern subarctic areas –Siberia, Alaska, Nunavut territory in Canada– where the predominant biome is tundra, as well as in the temperate grasslands, savannas and shrublands of central North America. As far as Arctic areas are concerned, in these ecosystems seasonality reduces plant production during part of the year, which explains why middle and big game constitute the primary food source for their inhabitants. In addition, secondary products of big game hunting, such as fat and oil, bones and skins, etc., are first need products given the low temperatures of those territories (Speth and Spielmann, 1983).

- **Cluster 3 (115/1290 societies): HGF – Fishers – H(26%)G(18%)F(49%)**

  Cluster 3 presents a foraging economy heavily reliant on fishing that is complemented with hunting; plants play a minor role in this group. The majority of societies from cluster 3 are geographically located in cold coastal areas whose biome is either tundra or taiga: northern Japan, southernmost South America (Tierra del Fuego), Arctic and subarctic areas (Russia, northern Canada, Alaska), which explains why gathering is so marginal. Also remarkable is the agglomeration of societies from this cluster that we find in the NW coast of North America –with a temperate conifer forest biome. Notably, waters in all these areas are extremely rich; Northern Pacific coasts, for instance, are part of the highest primary producer waters in the world (Koblents-Mishke, 1965). Such richness of fishery products together with the fact that winters in most of these territories translate into scarcity of terrestrial resources, justify the subsistence choice made by their peoples. Circumpolar and Inuit communities are paradigmatic examples of this cluster.

FARMING STRATEGIES

- **Cluster 4 (78/1290 societies): Pastoralists – Husbandry (62%) + Agriculture (17%)**

  Cluster 4 corresponds to the pastoralist strategy, i.e., that in which animal husbandry is the activity clearly prioritised. Such a great reliance on animal husbandry is combined with a 17% of dependence on agriculture –either to supplement human diet or to obtain fodder for their herds. The geographical location of the pastoralist societies in our EA sample points to an almost exclusive correlation between this subsistence economy and the deserts and xeric shrublands biome. Moreover, it would seem that pastoralism is an African-Asiatic strategy, since while it is the predominant subsistence economy in the arid lands from North and South Africa, the Arabian Peninsula, Kazakhstan and Mongolia, it has almost no presence in Europe, America and Oceania. Additionally, as it could be expected, most pastoralist societies are either nomadic or seminomadic.

- **Cluster 5 (613/1290 societies): Agriculturalists – Agriculture (62%) + Husbandry (20%)**

  Cluster 5 corresponds to the eminently agricultural strategy and it is by far the biggest one, encompassing almost 50% of the societies in our EA sample. Its distribution of percentages mimics that of the pastoralist cluster but in reverse, i.e., agriculture is the food source most heavily relied upon, and it is complemented with just a 20% of animal husbandry. Agriculturalist societies are present in the following biomes: tropical and subtropical moist broadleaf forests (Oceania, Southeast Asia, China, Bangladesh, India, Pakistan, the African Sahel, Central America, the external area of the Amazon basin); tropical and subtropical grasslands, savannas and shrublands as well as flooded grasslands and savannas (Central and South Africa); Mediterranean forests, woodlands and shrub (Mediterranean basin); temperate broadleaf and mixed forests (Central Europe and NE coast of North America); and temperate conifer forests (SW North America). Undoubtedly, agriculture is viable in a wide range of environments whose common denominator is that all of them are either tropical or warm areas with water availability.

It is also worth highlighting that an overwhelming majority of the societies in the present cluster have cereals as their major crop type, i.e., cereals constitute their food staples. Notably, even though agriculture in general –and staple agriculture in particular– customarily correlate with demographic increase, being as well regarded as the necessary condition for the emergence of sedentarism and hierarchical societies, it is also a fact that staple agriculture substantially increases both labour needs and socioeconomic risk (Stone and Downum, 1999); as a result of relying so heavily on a single economic activity, agricultural societies are known to experience more frequent famines than hunter-gatherers (Berbesque et al., 2014).

MIXED STRATEGIES

- **Cluster 6 (226/1290 societies):** ***Agrofishing*** **– Agriculture (51%) + Fishing (28%) + Husbandry (10%)**

  Cluster 6 presents a mixed economy in which half of the food resources are obtained from agriculture, constituting fishing the second major food source; this subsistence strategy is further completed with a minor contribution of animal husbandry. The type of agriculture practised by most societies in this cluster is horticulture, being roots/tubers and tree-fruits the most frequent crop types.

  As it can be seen in Fig. 15, the *agrofishing* strategy corresponds mainly to the biome of tropical and subtropical moist broadleaf forests. Remarkably, a relevant part of the societies is located in islands; more precisely, the islands in which we find *agrofishing* include Taiwan, the Philippines, Indonesia, most of the islands from Micronesia, Melanesia and Polynesia, as well as Madagascar and the Caribbean archipelagos. Additionally, we find *agrofishing* in Vietnam, Burma, Bangladesh, India, the African Sahel, Central America and the external area of the Amazon basin. Lastly, *agrofishing* communities are also found in the context of the African Great Lakes, where the biome is either flooded grasslands and savannas or tropical and subtropical grasslands, savannas and shrublands. The fact that this subsistence strategy is primarily found in coastal and riverine tropical areas may suggest that *agrofishing* is the result of the specific dynamics of those environments, namely their resource richness –recall that aquatic environments constitute some of the highest productivity areas in the planet (Nixon et al., 1986) – and their high climatic stability and resource predictability (Fitzhugh, 2003a). Eventually, an additional remark would be the geographical overlap that exists in various regions between *agrofishing* and the agricultural strategy -see for instance the Philippines, Indonesia, Vietnam, India, the Sahel and the African Great Lakes area, Central America and the external area of the Amazon basin-, which may denote the possibility of resource exchange between agriculturalists and *agrofishers*, a fact already suggested by several authors (Pestle et al., 2015; Svizzero and Tisdell, 2015).

- **Cluster 7 (98/1290 societies): *Whole Spectra Economies* (WSE) – H(25%)G(15%)F(17%) + Agriculture (40%)**

  Cluster 7 corresponds to what we have called *Whole Spectra Economies* (WSE), i.e., a subsistence economy that encompasses the two ends of the continuum –foraging on the one side and agriculture on the other– both with a similar relevance. More specifically, societies with a WSE present a 40% reliance on agriculture, being the distribution of percentages between the three foraging strategies –hunting, gathering and fishing– quite even. As far as location is concerned, WSE appear in a wide range of different environmental contexts: (i) the tropical and subtropical moist broadleaf forest biome –Papua New Guinea, the African Sahel, Central America, the peripheral territories of the Amazon basin–; (ii) the biome of flooded grasslands and savannas –African Great Lakes and the Parana basin–; (iii) the deserts and xeric shrublands biome –Gulf of California–; (iv) the biome of temperate broadleaf and mixed forests –New Zealand, the American Great Lakes region and the Mississippi basin–; and (v) the temperate conifer forest biome –Louisiana and the Florida Peninsula. The very different contexts in which WSE are found attest to their flexibility and adaptability to diverse circumstances. In particular, WSE are probably the most resilient of all the strategies found, given that their main defining trait is diversification, which might translate into a significant reduction of the risk of food shortages and famines.

Thus far we have analysed the seven clusters found at the mesoscale, and our main conclusion is that they could be divided into two main groups: *Primary Economies* and *Mixed Economies*. More precisely, we have realised that it is the internal distribution of dependencies on the different subsistence strategies that holds the key to distinguishing between the classical binary categories and the middle ground. This is because the configuration of such internal distribution ultimately informs about the different types and degrees of specialisation. Even though specialisation is usually defined in relation to the exploitation of a narrow subset of resources (Byers and Ugan, 2005), here we refer by specialisation to exhibiting high percentages of dependence –around 50%– on one to two subsistence strategies. Therefore, under *Primary Economies* we refer to those subsistence economies showing a strong reliance –i.e., a high specialisation– on one to two foraging or farming strategies –recall that for the case of two dominant strategies, both must be either foraging or productive. Consequently, the categories derived from the traditional HG-versus-farming divide fit reasonably well into this definition. Remarkably, in accordance with our results 75% of the societies in the EA present a primary economy, stemming the differences between the distinct primary-economy clusters from the strategy that is prioritised (if hunting is given priority over gathering/fishing, agriculture over animal husbandry, etc.). In this vein, it is also important to note that although the HG-agropastoralist disjunctive is already established by the first PCA dimension, further PCA dimensions have been considered for the identification and characterisation of the different clusters falling under primary economies.

On the other hand, we refer under *Mixed Economies* to all those subsistence economies that combine both foraging and productive strategies, and that generally rely on a wider spectrum of subsistence strategies (typically three or four). Additionally, as stated in the methods section, mixed economies can alternatively be defined as a function of the information entropy; more specifically, as a consequence of their reliance on a greater number of subsistence strategies, mixed economies correspond to those alternatives with higher/the highest information entropy. Unquestionably, the most distinguishing feature of mixed economies is the combination of foraging and farming within the same subsistence economy, something which does not occur among the primary economies, and which turns them into extremely valuable examples of what the middle ground may have looked like. Ultimately, it is remarkable that up to 25% of the societies in our EA database have a mixed economy; such a relevant percentage proves once again that instead of a single intermediate category between hunting-gathering and agriculture, mixed economies constitute a complex phenomenon worthy of study in its own right. Consequently, since one of the aims of the present contribution is to gain a better understanding of human subsistence variability in general, and of the middle ground in particular, hereunder we proceed to explore the particularities of the mixed economies in greater detail (for k = 15).

MIXED ECONOMIES FOR K = 15

As we saw in the results section, at k = 15 we find further divisions of the previous seven clusters that help profile more clearly the particularities of the different alternatives. However, as previously stated, here we will limit our discussion to those economies that we have defined as mixed.

In accordance with Fig. 14 -the sunburst diagram-, for k = 15 the *agrofishing* strategy is further divided into two clusters, and the same happens to the WSE. Consequently, in this section we will succinctly explore these four subdivisions, together with an additional cluster that is obtained after splitting the pastoralist cluster into two; (recall that this fifth cluster will be also delved into since it happens to perfectly match the definition of mixed economies too). For the details on their geographical location and entropy values please refer to Fig. 16 -map of the subsistence strategies with a relevant percentage of agriculture and/or husbandry for k = 15- and Table S 5 -the summary of information entropies for k = 15- respectively.

***Agrofishing* subdivisions:**

- **Cluster 6.A. (117/1290 societies): *Agro*(47%)*fishing* (37%) + Husbandry (7%).** In overall terms, this cluster could be described as the purely *agrofishing* strategy: the percentages of dependence on both agriculture and fishing are rather close, being the contribution of husbandry entirely marginal. Regarding their prevalent crop type, it is roots/tubers, followed by tree-fruits. The constituents of this cluster are mainly island societies living in tropical and subtropical moist broadleaf forests, except for those groups found in central Africa and in the external territories of the Amazon basin.

- **Cluster 6.B. (109/1290 societies): *Agro*(54%)*fishing*(20%) + Husbandry (13%).** This second *agrofishing* cluster corresponds to *agrofishing* inland societies; their subsistence economy is characterised by a predominance of cereal agriculture and a lower percentage of fishing that is compensated with a higher percentage of animal husbandry. The prevailing biome in which they appear is tropical and subtropical moist broadleaf forests.

WSE subdivisions:

- **Cluster 7.A. (49/1290 societies): *Agrohunting* + Fishing – Agriculture (45%) + Hunting (28%) + Fishing (18%).** This cluster presents a subsistence strategy in which plant resources are obtained from agriculture while animal products come from both hunting and fishing. Their crops consist of either cereals or roots/tubers with equal probability, and these societies are generally located in inland tropical and/or temperate ecosystems. One of their defining features is that they find themselves in the vicinity of lakes and big rivers. In this subsistence economy, the greater weight given to hunting with respect to fishing is likely to stem from their inland location –recall that even though lakes and big rivers provide exceptional fishing resources, their richness is not comparable to that of seas and/or oceans.
- **Cluster 7.B. (49/1290 societies): Paradigm of the Whole Spectra Economy – H(21%)G(25%)F(15%) + Agriculture (35%).** The characteristics of this WSE subdivision are very similar to those obtained for the WSE when $k = 7$. It is found across a wide range of different biomes, being their major crop type either cereals or roots/tubers with equal probability.

Pastoralist mixed subdivision:

- **Cluster 4.B. (39/1290 societies): Husbandry (49%) + Agriculture (22%) + Hunting (12%) + Fishing (11%).** This cluster corresponds to the second most mixed economy -the one with the second highest value of information entropy, only surpassed by that of the WSE (the paradigm of a mixed economy)-. Remarkably, this alternative is found in those biomes that are rather ill-suited for both agriculture and hunting: deserts and xeric shrublands and boreal forests, a fact that explains the great percentage of reliance on animal husbandry, as husbandry is famous for being highly resilient and successful in extremely adverse environments (Western, 1982).

The conclusions to be drawn from the different clusters into which mixed economies are subdivided for $k = 15$ may be summarised as follows:

(i) **Mixed Economies represent a complex phenomenon with multiple manifestations and significant internal variability.** When we defined *Mixed Economies*, we detailed their two distinctive characteristics, namely: (1) the combination of foraging and farming strategies within the same subsistence economy; and (2) the encompassing of a greater number of subsistence strategies (usually three or four). It is in the context of this second aspect that we find the greatest variability. An interesting way of looking at such variability is to arrange the different mixed economies along a gradient of increasing information entropy, or what is the same, increasing diversification. As it can be deduced from Table S 5, such a gradient would start with the *agrofishing* cluster 6.A. -which is admittedly a highly specialised alternative- and it would culminate with cluster 7.B., the paradigm of the Whole Spectra Economy -which constitutes the most diversified of all the subsistence strategies found-. Therefore, from this point we can conclude that all the subsistence economies encompassed under *Mixed Economies* are indeed quite different from each other, a fact that is perfectly aligned with the notion that the middle ground was actually much wider, diverse and complex than previously thought.

(ii) **Diversification as a risk-management strategy.** In those mixed economies encompassing a greater number of subsistence strategies, and most notably in those with similar percentages of dependence on the different sources considered -i.e., the ones with the highest information entropy-, diversification could in fact be a risk minimisation strategy, as complementarity allows to counterbalance possible shortages in specific resources (Jochim, 1981; Larson et al., 1994). Thereupon, the most diverse mixed economies would be the most flexible, resilient and reliable ones. Actually, risk and return maximisation appear to be managed differently in mixed vs. primary economies, since while mixed economies diversify, primary economies maximise return rates through specialisation, intensification and/or greater labour investment on a single subsistence strategy; an aspect which is in all likelihood linked to their different socioecological contexts, as specialist strategies work well in stable environments, while diversification is more suitable for settings with unpredictable environmental events (Ember et al., 2020).

(iii) **The role of fishing in shaping Mixed Economies.** Fishing is present to a greater or lesser extent in all the economies that are mixed. Clearly, this point is very closely linked to the previous one, since as noted by Larson et al. (1994), one of the major advantages of costal/riverine/lacustrine settlement is the ensuing reduction in the overall variance in food production, as a consequence of pooling the yields from different terrestrial and aquatic sources. Importantly, thanks to this risk-mitigation function, fishing could have been the key element around which mixed economies are structured, being at the same time responsible for their viability and long-term success. More precisely, as a result of the high carrying capacity of aquatic environments (Nixon et al., 1986; Bailey and Milner, 2002) -which translates into low risk and the easy attainment of greater returns by simply increasing labour investment and/or technological innovation-, fishing could have acted as a buffer against adverse disturbances, hence enabling to face climatic downturns (Lepofsky and Caldwell, 2013; Mathews and Turner, 2017), population increases and/or competitive social dynamics (Weitzel et al 2020) without substantially changing the economic structure -i.e., fishing would have conferred resilience to the socioeconomic system (Trosper, 2002;

Lancelotti et al., 2016), and thus, prevented and/or delayed the adoption of alternative subsistence economies such as fully agricultural ones-.

QUESTION 2: WHAT IS THE ROLE PLAYED BY ECOLOGICAL SETTINGS IN THE CONFIGURATION OF THE DIFFERENT SUBSISTENCE STRATEGIES?

There has been much debate about the role played by ecological variables in shaping human behaviour –see Nettle et al. (2013) and a review in Ahedo et al (2019). At present, one of the most widely accepted views is that even though they condition human agency, they do not determine it. In this line, despite human cultural variability might not be directly explained on the basis of ecological traits, it is true that ecological constraints shape subsistence activities (De Souza and Mirazón Lahr, 2015), and that these configure several social organisational aspects.

Given our omnivorous nature, human nutritional requirements can be fulfilled in very different ways. Here is where the environmental conditions come into play, since while several ecological contexts allow the development of different and/or flexible economic strategies, many others offer limited possibilities, condition the complementarity choices to be made and restrain population growth. More specifically, whilst the carrying capacity of some settings can be further increased just through innovation, diversification, specialisation and/or intensification (Morgan, 2015), in other contexts it is simply unfeasible to expand it –see for instance desertic areas in which agriculture cannot be put into practice. Nevertheless, it is important to note that not only the ecological variables set limits to growth; in fact, subsistence economies themselves present limitations as well, since they offer different growth possibilities depending on their structure. In HG societies with no food storage techniques, for instance, intensification is, to a major extent, limited, as increasing the hunting/gathering rates above the needs of the group would directly translate into those resources becoming spoiled (Mannino and Thomas, 2002; Wroe et al., 2004). By contrast, in fully agricultural societies with storage systems, a priori there would be no limitations to intensification other than those imposed by the land’s productivity and availability.

As far as our results are concerned, they show that specific socioeconomic choices appear recurrently in certain ecological systems. While this is obvious for coastal economies, our findings may also shed light into possible macro-behavioural patterns associated with human ecology, socioecological systems and their persistence. More specifically, in the cluster interpretation from question 1 –based on Fig. 15 and Fig. 16–, we found that (i) pastoralism and gathering are the prevailing subsistence strategies in arid areas; (ii) agriculture is extremely versatile, being viable in a wide range of biomes as long as they are warm and have water; (iii) the primacy of hunting appears recurrently in subarctic contexts; (iv) those HGF whose dominant strategy is fishing are commonly found in cold coastal areas; (v) in *agrofishing* strategies, the different percentages of dependence on fishing resources correspond to their inland or coastal location; and that (vi) WSE more heavily reliant on hunting correspond to inland locations in the vicinity of lakes and/or rivers. Additionally, these findings are in perfect coherence with the results from the group variable importance analysis –Fig. 19–, which show that from all the groups of variables considered, the group of the ecological variables is the most discriminant one. Lastly, as regards the results from the individual variable importance analysis –Fig. 18–, it is worth noting that even though the variable biome itself contributes just marginally to predicting the response –when the predictors are arranged by importance, it appears in the last third–, the fact is that many of the variables within the top half are to some extent related to the biome –see agriculture intensity, crop type, temperature and precipitation-related variables, resource richness, etc.

QUESTION 3: THE ROLE OF FISHING IN THE DEVELOPMENT OF VIABLE ALTERNATIVES TO CULTIVATION.

Archaeological and ethnographic narratives of the past 150 years have traditionally relegated fishing and aquatic-oriented societies to a marginal role; the reasons behind such relegation are to be found –among others– in (i) the postglacial sea-level rise –which submerged most of the shorelines older than 10,000 years B.P. and thus their archaeological evidence–, a fact that has led to assumption that aquatic resource exploitation emerged very late in human prehistory; (ii) the differential preservation and reporting of material evidence of aquatic adaptations –such evidence is very scanty as most tools were made from biodegradable materials, and its documentation is considerably patchy since aquatic resources were held to be economically unimportant¡; (iii) all the additional biases of the archaeological and ethnographic records; (iv) the predominant role attributed to hunting in most traditional hunter-gatherer models; and (v) the reluctance to abandon the deep-seated HG-farmer classification and the ladder of economic and technological progress it implies (Erlandson, 2001; Bailey and Milner, 2002).

However, the results of our analyses show that the role of fishing could have been far more relevant than previously thought. In fact, in all but the purest primary economies, the percentage of dependence on fishing is greater than 10%. For the resolution level corresponding to k = 7, we see that fishing constitutes a relevant source of food in 4 out of 7 (60%) of the clusters identified, being its contribution only marginal in clusters 2 –hunters–, 4 –pastoralists– and 5 –agriculturalists. This 60% ratio is maintained for k = 15, where the percentage of dependence on fishing is found to be either equal to or greater than 10% in 9 out of 15 of the clusters. In this vein, it is also remarkable that with the exception of the strictly fishing economies –i.e., the HGF heavily reliant on fishing and the sheer fishers–, the presence of fishing is a common factor across all those subsistence economies that diversify more, i.e., that are more ‘mixed’. As a matter of fact, if we look at the clusters obtained for k = 15, –please refer to Table S 5 in the Supplementary Material–, from cluster 6.A. (*agrofishing*) onwards, we identify both a gradient of increasingly mixed subsistence economies and the presence of a relevant percentage of fishing across all them. Therefore, we can assert that fishing is the common denominator of all the strategies lying between *agrofishing* and the WSE. Actually, *agrofishing* seems to play a ‘hinge’ role between the primary economies –i.e., those heavily reliant on one to two subsistence strategies and that generally correspond to the traditional stereotypes of HFG, pastoralism, agriculture and/or agropastoralism– and the mixed economies, the most paradigmatic of which is the WSE. Recall that this finding is aligned with previous contributions by Erlandson et al. (2006; 2010) and Lepofsky et al. (2013), in which they already noted that in accordance with recent findings, our ancestors would have relied on aquatic resources more heavily and for longer periods of time than the twentieth century anthropological theory once suggested.

As previously mentioned, aquatic environments (coastal, riverine and/or lacustrine) constitute exceptionally rich ecosystems (Bailey and Milner, 2002) in which –at least a priori– neither resource restoration nor limits of carrying capacity pose a problem, since both can generally be solved by simply enlarging and/or changing the catchment area. In these contexts, the main limitations are linked either to geographical constraints and/or to the development of specific nautical/resource-exploitation technologies. Due to all the above, aquatic environments can be considered singular locations that present very specific subsistence behaviours and that foster particular social dynamics.

Regarding subsistence economies, aquatic societies are known to have developed sophisticated management systems to sustain or increase resource diversity and/or yields. The broad spectrum of activities, actions and strategies encompassed under management systems may be organised around four main pillars: (i) harvesting methods –see for instance clam harvesting with digging sticks, *en masse* fish harvesting by means of weirs, traps and nets, the extension of harvest times through the construction of holding ponds into intertidal fish traps, the establishment of harvesting rules to prevent overharvesting, etc. (Lepofsky and Caldwell, 2013); (ii) enhancement strategies –such as transplanting eggs, size selection, habitat conditioning and extension: boulder clearance, construction of rock walls in the lowest intertidal zone to create clam gardens (Williams, 2006; Lepofsky et al., 2015), etc.; (iii) tenure systems –ownership of fish harvesting locations and/or rights to catch fish from certain areas (Turner and Jones, 2000); and (iv) world view and social realm –discouragement of overharvesting, pursuit of ecosystem equilibrium, initiation ceremonies (Mathews and Turner, 2017). In the ethnographic and archaeological records, paradigmatic examples of aquatic management techniques are documented –among others– for the Chulmun people in Korea (Lee, 2011), several coastal societies from the Atacama Desert (Flores et al., 2020) and indigenous peoples from both the NW Coast of North America (Caldwell et al., 2012) and the Southern Coasts of Eastern North America (Thompson and Worth, 2011).

As far as social dynamics are concerned, aquatic-oriented societies are typically characterised by their reduced mobility (Kelly, 1983, 1995) –which in most cases would have led to sedentarism or semi-sedentarism (Borrero and Barberena, 2006)–, their big population numbers (Sassaman, 2004; Lepofsky and Caldwell, 2013), and/or the emergence of social organisational changes such as higher territoriality (Yesner et al., 1980) and/or increased political complexity (Arnold, 1992; Marquet et al., 2012), traits long assumed to require agriculture to develop.

Eventually, we would like to return to the fact that as a consequence of their high resilience, successful aquatic/maritime adaptations could have acted as a viable alternative to cultivation (Zvelebil and Rowley-Conwy, 1984). Coastal/riverine/lacustrine societies would have retained their hunter-gatherer strategies or would have adopted different subsistence combinations strongly reliant on aquatic resources, since fishing would have been significantly more reliable and cost-efficient than other inland alternatives (Roberts et al., 2013; King et al., 2018). In this regard, it is also remarkable that the adoption of subsistence economies significantly dependent on fishing would not have been the immediate consequence of living in a coastal/aquatic environment; quite the contrary, it would have been the result of a thoughtful choice after carefully considering the risks and advantages of other alternatives; for instance, several examples attest to the retention of the original subsistence economies after having continuous contact with farming populations (Roberts et al., 2013; Svizzero and Tisdell, 2015; Díaz-Zorita Bonilla et al., 2016).

CONCLUSIONS

Current research on the transition to agriculture is characterised by both a burgeoning corpus of data and the pursuit of broader explanatory frameworks through the integration of different theoretical perspectives and the adoption of computational approaches. In this context, the present contribution proposes to explore prehistoric economies in general, and the middle ground in particular, through the quantitative analysis of ethnographically documented subsistence choices. More specifically, by means of both unsupervised and supervised learning techniques we have assessed (i) the viability and relevance of the different subsistence combinations, (ii) the existence of associations between specific subsistence economies and certain ecological settings, and (iii) the importance of fishing in the configuration of mixed economic choices. The main conclusions obtained may be summarised as follows:

1. Recurrent specific subsistence combinations have been identified via clustering in the EA subsistence dataset, which implies that not all combinations are viable. For the different levels of resolution considered, the subsistence economies found can be divided into two main groups: *Primary Economies* and *Mixed Economies*. Even though such divide may not seem innovative –since those designations have already been used in the literature–, the fact is that in contrast to all the previous contributions –most of which consist in case-based theorisation–, we propose a formal quantitative criteria –the information entropy– to determine whether a subsistence economy is mixed: the higher the information entropy value, the more mixed the subsistence economy.
2. Mixed economies are not a marginal choice. In fact, they represent up to a quarter of the cases in our EA subsistence dataset. In addition, the *Mixed Economies* group presents clear patterns of internal variability that are directly correlated with the diversification level of the different alternatives. Remarkably, such diversification may actually be a risk-management strategy that could be responsible for the high resilience characteristic of mixed economies.
3. Fishing as a subsistence strategy is more relevant than previously thought, being present in up to 60% of the different subsistence economies identified. In addition, fishing seems to be the key element around which mixed economies are structured, as it is the common denominator across all of them. Notably, given that aquatic environments are characterised by their high resource richness, fishing could have acted as a buffer against social and/or environmental contingencies, thus ensuring the long-term persistence of all the strategies of which it is part, and favouring their consolidation as viable alternatives to cultivation.

Ultimately, our contribution serves to illustrate the potential of advanced computational methods as theory-building tools; more precisely, we have showed that the application of machine learning techniques to a comprehensive standardised cross-cultural database such as D-PLACE can provide us with new insights into problems as relevant, complex and multidimensional as the transition to agriculture.

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SUPPLEMENTARY MATERIAL

Table S 1. Correlation coefficients and their respective *p*-values (in brackets) of the first PCA dimensions with the variables in the dataset: percentage of dependence on hunting, gathering, fishing, husbandry and agriculture.

PC Dim.	Hunting	Gathering	Fishing	Husbandry	Agriculture
1	0.806 (2.319e-295)	0.775 (5.286e-259)	0.551 (2.555e-103)	-0.593 (2.167e-123)	-0.848 (0.000e+00)
2	0.245 (4.834e-19)	0.346 (1.130e-37)	-0.670 (4.802e-169)	0.575 (3.079e-114)	-0.288 (3.905e-26)
3	-0.175 (2.579e-10)	-0.225 (2.525e-16)	0.495 (1.561e-80)	0.564 (4.256e-109)	-0.445 (7.917e-64)
4	0.510 (2.154e-86)	-0.478 (1.256e-74)	-	-	-

Table S 2. Optimal number of clusters proposed by elbow method, average silhouette method, gap statistic and NbClust following the majority rule.

Method	Optimal nb. of clusters
Elbow method	2
Average silhouette method	2
Gap statistic	9
NbClust (majority rule)	2

Table S 3. Most frequent alternatives proposed as the optimal number of clusters by the 30 different indices computed by NbClust. Note that this table is some sort of contingency table and that proposals receiving just one vote have not been included.

Optimal nb. of clusters	Nb. of NbClust indices proposing it
2	6

3	5
4	2
5	4
15	3

S1 APPENDIX – CHOICE OF *K* = 7 AND *K* = 15.

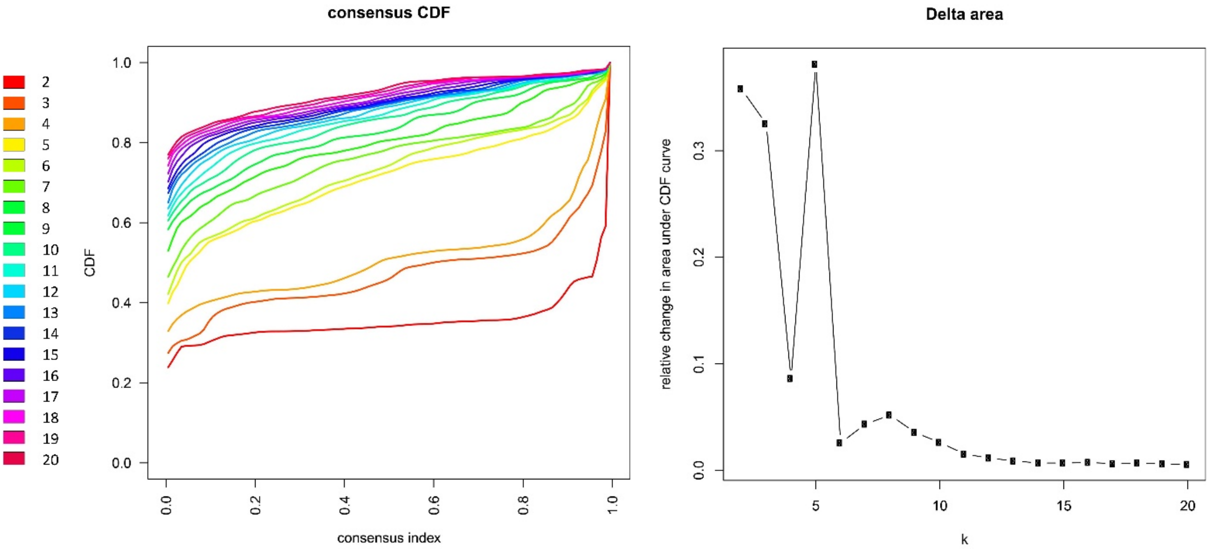

Figure S 1. Cumulative distribution functions (CDFs) obtained for the different k's (left), and delta area function (right), which shows the increase in the area under the CDF with increasing k.

As stated in the Results section, the assessment of the evolution of the CDFs and of the delta function –both showed in Figure S 1– lead us to the identification of two levels of interest: (i) the one ranging from *k* = 5 to *k* = 10 and (ii) that ranging from *k* = 11 up to *k* = 20.

As far as level (i) is concerned, at *k* = 5 we find the steepest increase in the area under the CDF; the ensuing *k*'s up to *k* = 10 do also translate into an increase in the area under the CDF, but of a significantly smaller magnitude. Therefore, we opted for *k* = 7 to explore level (i) since even though in accordance with the delta area one would probably choose *k* = 8, the consensus matrix obtained for *k* = 7 is undoubtedly more diagonal-block and cleaner –hence denoting more cluster stability– that the one for *k* = 8. To see the consensus matrices obtained for *k* = 2 to *k* = 20 please refer to the folder *Consensus matrices & CDF* available at our GitHub repository: https://github.com/Virahe/Lets-go-Fishing.

Regarding level (ii), it seems to saturate after *k* = 13, being the increases in the area under the CDF after that value indeed very small; however, we chose the intermediate value of the interval, i.e., *k* = 15, since again even though according to the delta function one would probably choose *k* = 13, the consensus matrix for *k* = 15 is in fact more diagonal-block and consequently the cluster structure is likely to be more stable.

Table S 4. Summary table for k = 2. It includes cluster number, each cluster's average strategy, -the average of the percentages of dependence on gathering, hunting, fishing,

husbandry and agriculture across all societies in the cluster-, their entropy, standard deviation, the number of variables with a percentage of dependence equal or greater than 15% and 10%, and a succinct interpretation of the cluster. Note that the table has been sorted in ascending order of entropy.

	Clusters' average strategies (Mean values per variable and cluster)									
Cluster nb	Gathering (%)	Hunting (%)	Fishing (%)	Husbandry (%)	Agriculture (%)	Entropy	SD	Limit 15	Limit 10	Interpretation
2	5,73	9,43	11,96	19,29	53,58	1,29	19,42	2	3	Agriculture & Husbandry
1	30,78	33,75	29,32	2,68	3,47	1,30	15,54	3	3	HGF

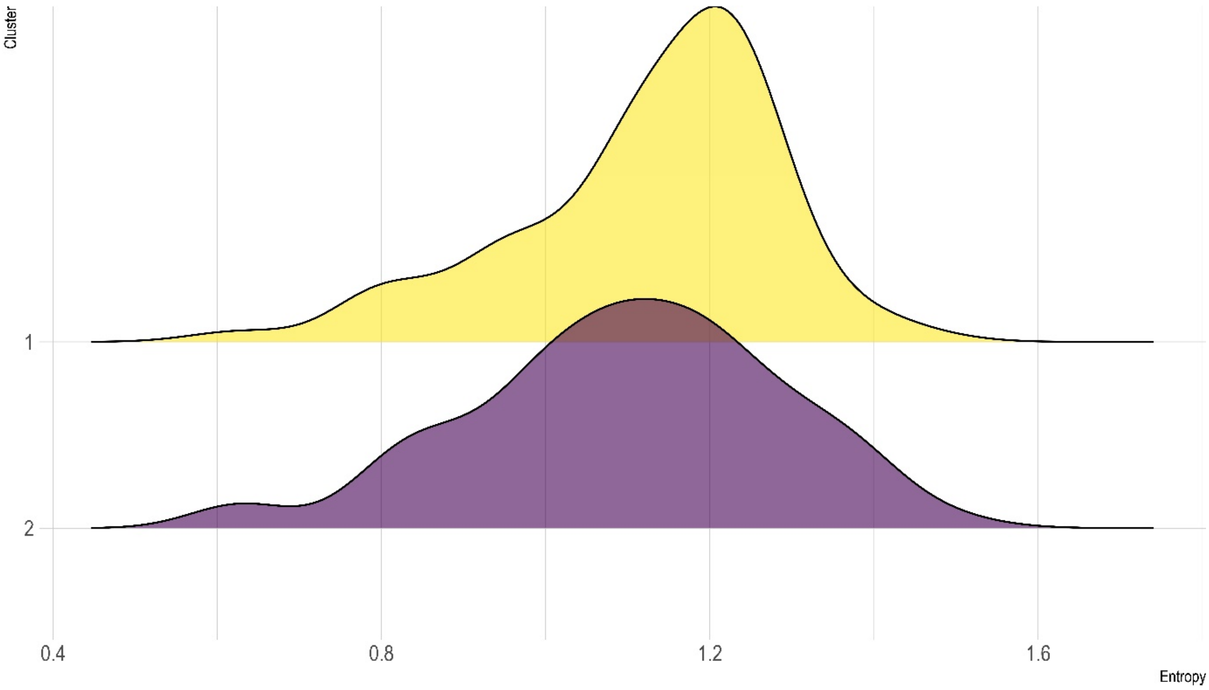

Figure S 2. Ridgeline plot of the entropy distributions of each cluster for k = 2. Recall that the distributions have been sorted in ascending order of entropy along the vertical axis.

Table S 5. Summary table for k = 15. It includes cluster number, each cluster's average strategy, -the average of the percentages of dependence on gathering, hunting, fishing, husbandry and agriculture across all societies in the cluster-, their entropy, standard deviation, the number of variables with a percentage of dependence equal or greater than 15% and 10%, and a succinct interpretation of the cluster. Note that the table has been sorted in ascending order of entropy.

	Clusters' average strategies (Mean values per variable and cluster)									
Cluster nb	Gathering (%)	Hunting (%)	Fishing (%)	Husbandry (%)	Agriculture (%)	Entropy	SD	Limit 15	Limit 10	Interpretation
4.A.	2,88	6,58	2,90	75,02	12,62	0,86	31,01	1	2	Husbandry (75%) + Agric. (13%)

2.BIS.	16,40	69,82	8,50	2,64	2,64	0,95	28,42	2	2	Hunters - H(70%)G(16%)F(9%)
3.A.	5,32	13,85	71,65	4,28	4,90	0,95	29,14	1	2	Fishers - H(14%)F(72%)
1.A.	56,58	31,60	5,20	2,64	3,99	1,06	23,72	2	2	HG Gatherers - H(32%)G(57%)
5.A.	4,23	5,22	5,84	21,98	62,73	1,08	24,99	2	2	Agro(63%)Pastoralists(22%)
3.B.	7,97	39,03	48,09	2,57	2,34	1,10	21,86	2	2	Hunter-Fishers - H(39%)F(48%)
5.C.	5,89	11,59	6,93	9,72	65,87	1,10	25,74	1	2	Agro(66%)Hunting(12%) + Husb.(10%)
5.B.	3,47	7,52	4,03	34,88	50,11	1,15	21,28	2	2	Agro(50%)Pastoralists(35%)
6.A.	3,75	5,67	36,72	7,28	46,58	1,20	20,11	2	2	Agro(47%)Fishing(37%) + Husb.(7%)
3.C.	25,78	23,16	45,14	2,47	3,45	1,25	17,73	3	3	HGF - Fishers - H(23%)G(26%)F(45%)
6.B.	5,73	6,62	20,27	13,11	54,29	1,26	20,04	2	3	Agro(54%)Fishing(20%) + Husb.(13%)
1.B.	36,68	34,82	22,28	2,64	3,58	1,28	16,39	3	3	HGF - H(35%)G(37%)F(22%)
7.A.	5,50	28,12	17,91	3,93	44,54	1,31	16,89	3	3	Agro(45%)Hunting(28%) + Fish.(18%)
4.B.	5,99	12,43	10,65	48,75	22,18	1,35	17,12	2	4	Husbandry (49%) + Agric. (22%) + H(12%)F(11%)
7.B.	24,91	20,98	15,01	3,66	35,44	1,45	11,78	4	4	H(21%)G(25%)F(15%) + Agric.(35%)

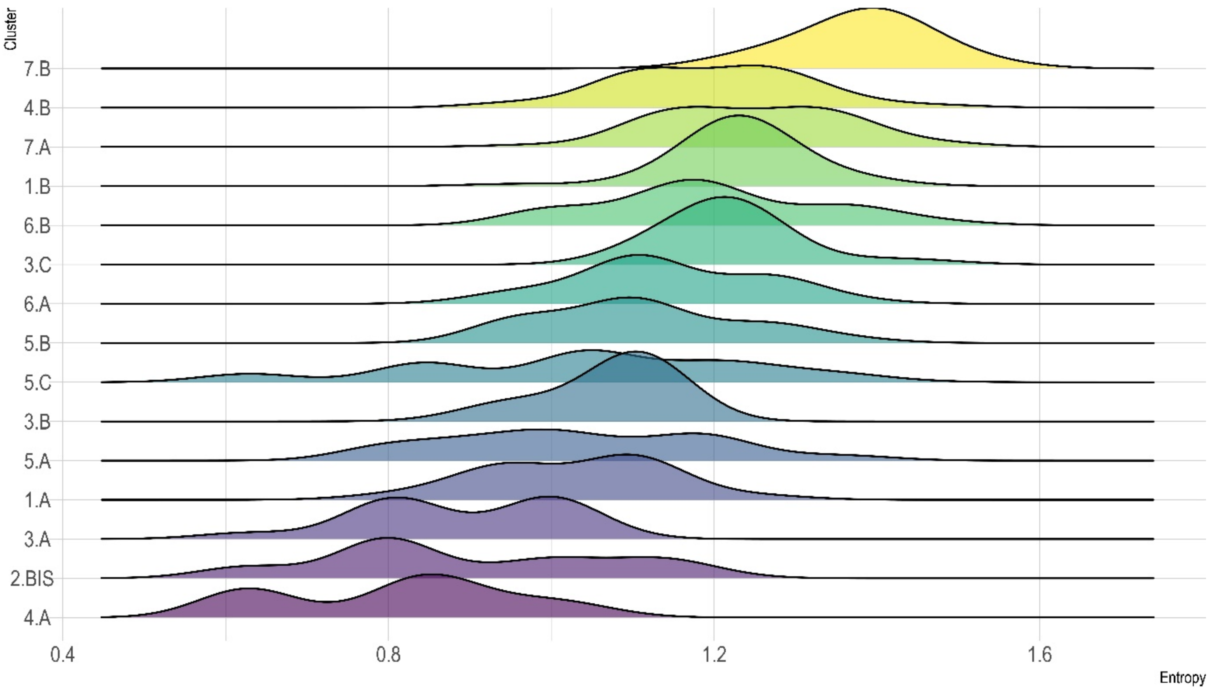

Figure S 3. Ridgeline plot of the entropy distributions of each cluster for k = 15. Recall that the distributions have been sorted in ascending order of entropy along the vertical axis.

CONCLUSIONS

7. CONCLUSIONS

This thesis was initiated with the overall aim of applying complex systems analysis techniques to integrative standardised databases from the fields of Ethnography, Anthropology and Archaeology, to explore, model and/or analyse different theories and hypotheses of relevance in those fields. Thereupon, the thesis intended to advance science at two levels: (i) a more general level related to the fact that the application of complex systems analysis methodologies in the three above-mentioned fields is in itself innovative; and (ii) a more specific level related to the particular scientific questions that each of the research articles constituting this thesis address.

In the light of the work carried out within the framework of this thesis, which has resulted in four scientific articles, we can confidently state that its intended objectives have been successfully met.

The following sections summarise the different conclusions that may be derived from this doctoral thesis. Remarkably, given the two-level nature of its contributions to the advancement of science, its conclusions can also be structured around two levels of resolution: (i) general conclusions related to the overall objective of the thesis; and (ii) article-specific conclusions, i.e., the particular conclusions obtained in each of the four scientific articles. This chapter is entirely devoted to the general conclusions, as the specific conclusions reached in each article are duly explained in each of them.

Notably, we have divided these general conclusions into two blocks: methodology-related conclusions and lessons learned & important remarks.

7.1 METHODOLOGY-RELATED CONCLUSIONS

- The methodological framework used in this thesis has been referred to as *the complex systems analysis toolbox*, since it consists of different analytical tools and methods that are useful for the analysis of complex systems. Thereupon, it is generic enough so as to be extrapolated to the study of other complex systems different from the ones addressed in this thesis. Nevertheless, it should be noted that in the present thesis we have only considered those analytical tools that were of interest for the systems and research questions at hand. Consequently, the study of different systems/questions may require the consideration of additional tools and/or new analytical developments.

- The second article of this doctoral thesis, namely "Robustness assessment of the 'cooperation under resource pressure' (CURP) model" has served to illustrate both (i) the potential and utility of the ABM paradigm to build virtual computational social worlds with which we can experiment, test hypotheses against empirical data and/or attain generative explanations; and (ii) the relevance of the verification and validation of those ABM models. More specifically, in this thesis we have elaborated on the inherent complexity of ABM models, which makes it difficult to understand which parts of the model generate a particular set of outcomes, thus making ABM models particularly prone to errors and artefacts. Accordingly, it becomes essential to develop and embrace systematic approaches for their validation and verification so as to better understand the model itself, to improve its reliability and to increase our confidence in the results obtained.

- Supervised learning techniques have been extensively used in three out of the four articles of this thesis. In this regard, the most important conclusion is related to the great potential of supervised learning in general, and of regression and classification models in particular, not only for predictive purposes –their usual intended use–, but also as explanatory tools useful for the detection of patterns, relationships and/or anomalies – i.e., points that do not follow the general pattern–. Remarkably, in the presence of such anomalous cases, a thorough analysis of them may serve to shed light into the specific reasons that make them “special” and/or to identify new research questions and future research directions –see for instance the example in article 1–.

- Unsupervised learning techniques are conceived to look for structure in data in the absence of a predefined output variable. As evidenced in the fourth article of this thesis, namely "Let’s go fishing: a quantitative analysis of subsistence choices with a special focus on mixed economies among small-scale societies", unsupervised learning approaches may provide valuable insights into the matter at hand, particularly when we are faced with a raw database in which we do not know exactly what we are looking for. Notwithstanding, it should also be noted that unsupervised learning approaches are particularly susceptible to include the biases of the researcher into the study, as the absence of an output variable that guides the analyses will typically lead her to draw on her previous knowledge and/or preconceived ideas. Therefore, it is important to emphasise the tentative nature of assertions that can be made on the basis of unsupervised learning results, and the need to adopt a cautious and critical attitude for their interpretation.

- In relation to the Network Science paradigm and its potential usefulness within the fields of Ethnography, Anthropology and Archaeology, its greatest strength is to be found in the fact that it enables the formalisation and subsequent consideration of the relational dimension of problems, an aspect commonly disregarded in those fields. Consequently, network approaches allow to look at both traditional problems and new research questions from a different perspective, which may provide relevant insights and/or serve to explore previously uncharted areas –as we did in article 3 by means of the sharing similarity network–.

- This thesis in general, and articles 3 and 4 in particular, underscore the desirability and feasibility of multi-methodological approaches. More specifically, these two articles illustrate how the integration of complementary analytical approaches provides a more complete view of the problem at hand, serving at the same time to increase our confidence in the results obtained –recall that the fact that different methods identify the same pattern and/or produce identical results is taken as strong support to the hypothesis of its existence/veracity–. On the other hand, should the different approaches produce different/incompatible results, then we would have brought into light the lack of robustness of those results and/or the possibility of errors/artefacts in the models considered, the calculations made, etc. All in all, the adoption of multi-methodological approaches constitutes a very rigorous strategy, being it highly advisable to opt for it whenever possible.

7.2 LESSONS LEARNED & IMPORTANT REMARKS

LESSONS LEARNED FROM THE ANALYSIS OF ETHNOGRAPHIC/ARCHAEOLOGICAL EVIDENCE –ARTICLES 1, 3 AND 4–:

- In Ethnography, Anthropology and Archaeology assembling large-scale quantitative databases is extremely time-consuming, as it requires the in-depth analysis and consultation of multiple sources –publications, manuscripts, official reports, thesis, etc.– that are typically descriptive, and their subsequent translation into quantitative data. For this reason, even though at first glance the analyst may perceive the size of the database as small –specially in comparison to the massive ICT-enabled databases that are commonly analysed using the same methodologies–, it is important not to lose sight of the nature of the field(s) and of its subsequent limitations. In this vein, the take-home message would be that –at least a priori– the use quantitative computational approaches to explore ethnographic, anthropological and/or archaeological data should not be dismissed on grounds of the sample size. The only thing to bear in mind is that the results thus obtained will have to be interpreted very cautiously, and even more so if general conclusions are to be drawn from them.

- Closely related to the previous point is the problem of the fragmentary nature of evidence. Remarkably, in Ethnography, Anthropology and Archaeology this problem is even more pronounced, which translates into most databases from these fields having missing data. Traditionally, the existence of missing data has been considered an obstacle to the application of advanced quantitative analyses techniques, thus hampering the progress of this kind of research in the three above-mentioned disciplines. At present, we count with various techniques for missing data imputation –such as Multivariate Imputation by Chained Equations (MICE) (van Buuren et al., 1999; Buuren and Groothuis-Oudshoorn, 2011b) and single-imputation (Stekhoven and Buhlmann, 2012)– which help us overcome this problem and hence contribute to the development of this line of research.

- In view of the fact that ethnographic/anthropological/archaeological evidence is necessarily fragmentary and scanty, and fully aware that it may indeed be subject to different biases related to historical periods, the gender/nationality of the researcher, different research interests, etc., it becomes evident that the power of claims made on the basis of a particular set of evidence is markedly contingent and limited. Therefore, one has to be especially cautious when interpreting the results obtained from evidence-based quantitative analyses and should avoid the extrapolation of those results to areas where the attained conclusions may not be valid. In this regard, it is noteworthy that only when the results of the analyses constitute potential falsifiers of a given hypothesis –in the purest Popperian sense– may the claims be made more categorically.

LESSONS LEARNED FROM THE APPLICATION OF COMPLEX SYSTEMS ANALYSIS TOOLS TO ETHNOGRAPHIC, ANTHROPOLOGICAL AND ARCHAEOLOGICAL DATA:

- The challenge of interdisciplinary research. The adoption of interdisciplinary approaches –such as the one of the present thesis– is markedly advantageous in the sense that it allows for a more comprehensive understanding of the problem at hand thanks to the combination of different backgrounds and perspectives coming from multiple disciplines. However, on the other hand, it constitutes a significant challenge in several respects that include –but are not limited to–: (i) the need for time so that the different researchers involved learn to understand each other's disciplines, find a common language and create a common arena from which to transcend the disciplinary boundaries; (ii) the steep learning curve characteristic of interdisciplinary enterprises; (iii) the highly frequent negative results that may be obtained –particularly in the first stages of interdisciplinary projects–; and (iv) the funding barriers that may be encountered.

- The complex nature of social problems. It is a relatively plausible possibility that the true cause may not be included in the analyses –either because we do not know it or because no data are available–. It is also possible that aspects that are indeed relevant for the comprehension of a given phenomenon may not be considered in the analyses/models because we lack the mathematical developments/methods necessary for their analysis.

- The impact on the results of the scale of analysis selected and/or of the methodology adopted. The fact that we do not find patterns at a given scale and/or with a given analytical method/approach does not exclude the possibility that at different scales of resolution and/or with different approaches other relations may exist. We have to be aware that our choices may actually influence the knowledge that we are able to attain.

7.3 AREAS FOR FUTURE WORK

Given the strongly methodological character of the present thesis, plenty of future research lines may be devised in relation to the application of further complex systems analysis tools and/or to the adoption of additional formal approaches in the fields of Computational Social Science and the Digital Humanities in general, and in Ethnography, Anthropology and Archaeology in particular. More specifically, three of the future research lines that we think may hold the greatest potential are:

- The analysis of causality. Thus far we have focused on the identification and interpretation of different types of relations between variables. The next logical step would consist in the identification of the causal relations between them.

- Use of dynamic and multimodal networks. In the present thesis we have just focused on unimodal networks and we have disregarded their temporal dimension. Nevertheless, in future studies it could be of interest to assess the evolution of a network over time –that is what dynamic networks are suited for– and/or to consider different types of nodes and edges within the same network –multimodal networks–.

- Combination of text-mining with Network Science approaches. Text mining academic articles from the fields of Ethnography, Anthropology and Archaeology and subsequently analysing the results obtained by means of network approaches may serve to identify communities of deeply intertwined concepts, the most relevant concepts in the field, biases, knowledge gaps, the evolution of research interests over time, etc. To that end, the dynamic and multimodal network approaches explained in the previous point may be prove extremely useful.

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