Journal of Archaeological Science 181 (2025) 106329

Contents lists available at ScienceDirect

Journal of Archaeological Science

journal homepage: www.elsevier.com/locate/jas

Network entropy as a key to the past: A quantitative approach to complex social networks

Joaquín Jiménez-Puerto [a,*], Óscar Trull [b], Eamonn Devlin [c]

[a] Prehistory, Archaeology and Ancient History Department, University of Valencia, Spain
[b] Statistics, Applied Operational Research and Quality Department, Polytechnic University of Valencia, Spain
[c] National Center for Scientific Research Demokritos Greece, Greece

ARTICLE INFO

Keywords:
Entropy analysis
Adaptive cycle model
Network analysis
Phase identification
Complex systems
Copper age

ABSTRACT

The quantification of adaptive cycles in complex systems remains a significant challenge, particularly in archaeological contexts where traditional approaches rely heavily on qualitative assessments. This paper presents PANARCH (Phase Analysis of Network Adaptive Research & Complex Hierarchies), a methodological framework that integrates four complementary entropy measures—degree, eigenvector, community, and betweenness entropy—to identify and quantify adaptive cycle phases in complex networks. The framework enables systematic detection of phase transitions and provides mathematical signatures for different system states, advancing beyond single-metric analyses. We validate this approach through a detailed case study of archaeological networks from Eastern Iberia (5300-3800 cal BP), analyzing lithic arrowhead similarity patterns across multiple temporal windows. The results reveal structured patterns of social transformation, with entropy variations successfully identifying different phases of the adaptive cycle. PANARCH demonstrates particular utility in archaeological contexts where preservation biases often complicate traditional analyses, while offering broader applications for studying complex system dynamics across disciplines where phase transitions and system reorganization are key concerns.

1. Introduction

Complex Systems Theory (CST) provides a robust theoretical framework for understanding how systems respond and adapt to perturbations. CST recognizes that complex systems comprising interconnected elements have emergent properties beyond their individual parts. Building upon these foundations, Resilience Theory (RT) has emerged as a robust analytical framework for understanding how past societies responded to large-scale perturbations, primarily operationalized through the Adaptive Cycle Model (ACM).

This theoretical perspective has gained considerable traction in archaeology, generating substantial academic output (Bentley and Maschner, 2003; Bernabeu et al., 2012; Daems, 2021; Kohler, 2011).

Recent advances in network analysis have reshaped the study of complex adaptive systems. While early approaches relied on classical concepts such as thermodynamic entropy (Prigogine et al., 2017) and entropy metrics (De Aguiar et al., 2005; Ulanowicz et al., 2009), contemporary developments have embraced a multidimensional perspective.

The pioneering work of Castell and Schrenk (2020) established a milestone by introducing information theory concepts to quantify adaptive cycles. Integrating multiple entropy metrics represents a substantial innovation, providing a more comprehensive framework for analyzing systemic dynamics (Bianconi, 2018; Newman and Girvan, 2004).

However, significant methodological challenges remain in quantifying adaptive cycles. Current analyses predominantly rely on qualitative approaches, and even when quantitative methods are employed, they rarely incorporate comprehensive network metrics (Bradtmöller et al., 2017; Grimm et al., 2017). Traditional approaches focused on isolated measurements, missing the multidimensional nature of social dynamics.

To address these limitations, we propose a novel methodological framework that integrates multiple dimensions of structural entropy through SNA. This method allows us to quantitatively characterize adaptive cycle phases, keeping the complex interconnections of social systems.

To validate our methodological framework, we examine diachronic

* Corresponding author.
E-mail address: joaquin.jimenez@uv.es (J. Jiménez-Puerto).

https://doi.org/10.1016/j.jas.2025.106329
Received 20 November 2024; Received in revised form 26 April 2025; Accepted 19 July 2025
Available online 7 August 2025

network series previously analyzed through traditional SNA methods (Jiménez-Puerto, 2024). This comparison serves two purposes: testing our enhanced entropy-based metrics and allowing direct comparisons with established techniques.

In the following sections, we first explore the theoretical foundations and historical development of Social Network Analysis in archaeology before examining how this analytical framework can enhance our understanding of resilience and adaptive cycles in archaeological contexts. This integrated approach offers new possibilities for understanding the complex dynamics of past societies through quantitative analysis of their material remains.

1.1. The study of social complexity through social network analysis

In its most fundamental conception, a network represents a metaphor for connectivity. It consists of nodes representing elements of complex systems, connected by links showing relationships between them. Networks represent interactions between individuals and groups in human societies (nodes) (Wasserman y Faust, 1994: 4). Network structures exhibit a delicate balance between randomness and order, where stochasticity—the probabilistic nature of systems—coexists with organizing principles that ensure functionality.

Network Science posits that a complex system's underlying structure contains information about its function. While its methodological toolkit includes network inference and structural characterization, it transcends mere topology to identify networks' effects on social processes and predict complex systems' behavior (Bianconi, 2018).

Networks are fundamentally relational. Represented objects can encompass anything (archaeological sites, words, bacteria, etc.), while relationships can reflect various concepts (exchange, contagion, belonging, etc.). An illustrative metaphor considers objects as nouns in a sentence, with relationships serving as verbs. Social Network Analysis (SNA) fundamentally aims to describe structural properties through these relationships (Brughmans and Laguna-Palma, 2023; Jiménez-Puerto, 2022).

The early 21st century has witnessed SNA's dramatic rise in popularity, bolstered by theories of non-linear dynamics and complexity. The method continues to expand, with recent significant steps toward establishing a solid, homogeneous theoretical framework (Brughmans and Peeples, 2023). This development builds upon earlier foundations in sociometry, which emerged in the 1930s as a method for measuring interpersonal relationships in small groups, describing group structures through points and lines in two-dimensional space (Brughmans, 2013). By the late 20th century, Wasserman and Faust (1994a,b) formulated foundational principles for SNA applications, clearly specifying its social scope and establishing it as a multi-scale analytical tool.

Although graph theory techniques have been employed in archaeological research since the 1960s (Clarke, 1962; Kendall, 1969, 1971), early applications primarily focused on relationship visualization rather than analysis. Early applications share with modern SNA an emphasis on linking social assumptions to graph theory, though early archaeological applications (Irwin-Williams, 1977) had limited impact on subsequent network-related research. Today, formal SNA methods for archaeology are on the verge of having a coherent methodological corpus for testing hypotheses about social structures represented in graphs (Brughmans and Peeples, 2023; Collar et al., 2015; Knappett, 2011).

Few anthropological questions cannot be explored through a relational approach. Incorporating SNA into anthropological toolkits has led archaeological schools to adopt Complex Systems postulates. This approach allows archaeologists to characterize structures based on relational data. Complexity inherently characterizes all human societies, regardless of technological development (Reynoso, 2011), offering interpretative potential for understanding properties like emergence and non-linearity (Bernabeu et al., 2012; Daems, 2021; Davis, 2024; Kohler et al., 2017).

Beyond complexity theory, Actor-Network-Theory (ANT) has significantly influenced archaeology's use of network metaphors for social analysis (Latour, 2007; Van Oyen, 2015, pp. 63–78). While SNA and ANT represent distinct models, they share a grammar worthy of future exploration. Hodder's (2012) network-based analytical metaphor offers another perspective, theorizing about network-based representation (Hodder and Mol, 2016). However, mathematical representation alone doesn't guarantee correct interpretation or conclusive insights. SNA remains fundamentally an analytical technique, independent of specific theoretical movements and frameworks in archaeology (Reynoso, 2011), though every methodology necessarily requires grounding in a theoretical framework.

SNA's structural approach to social entities has proven particularly valuable in addressing the long-standing structure-agency debate in social sciences (Archer, 1995; Bourdieu, 2020; Giddens, 1979, 1984). Agency, or the ability of individuals to act freely, contrasts with stable structures that shape choices, which are well-documented in archaeology (Barrett, 2012; Dobres and Robb, 2000). These concepts represent different system levels in social contexts. At its simplest, the micro-level corresponds to individual system agents, the meso-level to agents interacting with communities, and the macro-level to community-community interactions (Rivers, 2016). Network theory and SNA excel here by integrating both spheres: macro (structure) and micro (agency).

These concepts represent different system levels in social contexts. At its simplest, the micro-level corresponds to individual system agents, the meso-level to agents interacting with communities, and the macro-level to community-community interactions (Rivers, 2016). Network theory and SNA excel here by integrating both spheres: macro (structure) and micro (agency). This capability makes SNA ideal for analyzing complex social systems and linking individual actions to broader patterns.

2. Theory and method

Understanding complex system dynamics requires sophisticated analytical tools that can capture both structural patterns and evolutionary processes. Our methodological framework integrates adaptive cycle theory, social network analysis, and entropy-based metrics to quantify and characterize system states and transitions.

2.1. Adaptive cycles and network structure

While Complex Systems Theory provides theoretical foundations for understanding complex systems, Resilience Theory (RT) offers a framework for understanding and characterizing their evolution (Folke, 2006; Gunderson, 2003; B. Walker et al., 2002). Initially developed in Ecology (Holling, 1973) and Psychology (Garmezy, 1985), resilience refers to a system's ability to absorb disturbances and keep its structure and function (Johnson et al., 2011; B. H. Walker et al., 2006). RT has proven particularly valuable for studying socio-ecological systems, with applications across economics, genetics, and archaeology, though it still lacks a unified application corpus (Bradtmöller et al., 2017; Perrings, 2006; Weinelt et al., 2021).

The Adaptive Cycle Model (ACM) represents the primary operationalization of RT (Holling and Gunderson, 2002) describing how complex systems evolve through four phases (see Fig. 1).

- Growth/exploitation (r)
- Conservation (K)
- Release/dissolution (Ω)
- Reorganization/renewal (α)

The phases of ACM depend on resilience, shaped by two main variables: potential and connectedness (Holling, 2001). Potential represents a system's available options based on skills and relationships, while connectedness quantifies the degree of internal control and rigidity in system relationships.

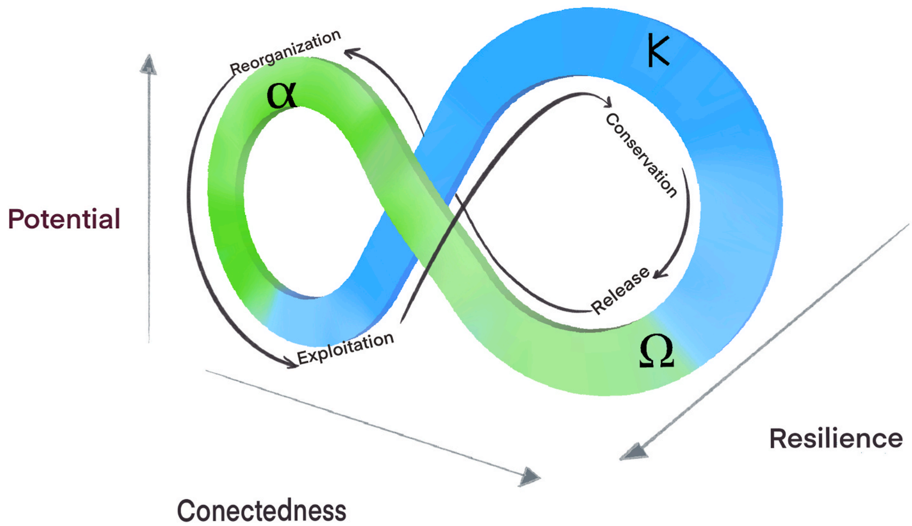

Fig. 1. Representation of Gunderson and Holling's Adaptive Cycle Model.

Network analysis provides tools to measure both variables: connectedness through metrics like density and clustering, and potential through measures of structural diversity and hierarchical organization. High connectivity indicates greater efficiency in system communication and adaptation, while potential reflects a network's capacity to adapt to new conditions (Grimm et al., 2017).

While most studies employ ACM as a conceptual heuristic model (Weiberg, 2012), recent research has attempted quantitative applications (Gronenborn et al., 2017; Hofmann, 2019; Shennan et al., 2013; Turchin, 2003; Weinelt et al., 2021). Various approaches have emerged to quantify these parameters: some define connectedness through subsistence, mobility, and social organization intensity, with potential representing innovation capacity (Rosen and Rivera-Collazo, 2012), while others view them as opposing aspects of social homogeneity (Grimm et al., 2017).

Network analysis has been used to examine connectivity between areas and broader systems (Collar et al., 2015), and analyze population dynamics (Maier, 2015). Recent archaeological approaches have proposed using network robustness analysis for studying adaptive cycles (Jiménez-Puerto and Bernabeu-Aubán, 2023), while advances in ecology suggest using Information Theory postulates for quantifying potential and connectedness (Castell and Schrenk, 2020).

This alignment between ACM variables and network properties provides the foundation for our quantitative approach.

2.2. Theoretical foundations of network entropy

The concept of entropy, initially formulated in thermodynamics by Clausius (Clausius, 1865a, 1865b), underwent a fundamental transformation with Shannon's information theory (Shannon, 1948). Applying entropy to network analysis extends these principles, but requires careful consideration of correlations and interactions between nodes, as network structures inherently contain dependencies through their connectivity patterns.

While our entropy calculations quantify the heterogeneity of various network properties, we acknowledge they are not thermodynamic entropies in the physical sense. The presence of correlations in social networks means these measures should be interpreted as relative indicators of structural diversity rather than absolute entropy values. This approach remains valid for comparing system states over time, as correlations systematically affect all measurements.

This methodological approach is justified through some key considerations. The entropy calculations serve as relative measures rather than absolute physical entropies, allowing us to track structural changes in network organization. By analyzing the same system over time, we ensure that network correlations systematically affect all measurements, maintaining the validity of temporal comparisons. This relative framework enables us to identify meaningful transitions in network structure while acknowledging the inherent dependencies in social systems.

Applying entropy to network analysis extends these principles naturally, providing robust mathematical tools for quantifying structural and organizational complexity in networked systems (Newman, 2012). In complex networks, entropy is a fundamental measure of uncertainty and heterogeneity in the distribution of connections and structures (Bianconi, 2018), proving particularly valuable in social systems analysis, where structural organization plays a crucial role in system function (Wasserman y Faust, 1994).

Applying entropic measures in network analysis has revealed fundamental properties of complex systems. Regarding structural organization, entropy provides a quantitative measure that transcends simple topological metrics, reflecting a balance between order and randomness.

Recent research has demonstrated entropy's effectiveness in analyzing temporal network evolution, with changes in network entropy serving as indicators of phase transitions in complex systems (Castellano et al., 2009). Systems with high entropy demonstrate greater resistance to random failures, while those with low entropy show increased vulnerability to targeted disruptions (Albert et al., 2000). This relationship between entropy and system stability makes it particularly relevant for studying adaptive cycles, where system reorganization and stability are key concerns.

Applying entropy metrics to adaptive cycle analysis is a significant innovation. Degree entropy, for instance, indicates a system's potential, reflecting the diversity of available connections and, thus, the options for adaptation (Ulanowicz et al., 2009). A system in the reorganization phase (α) typically shows increasing degree entropy values, indicating the exploration of new connections. On the other hand, community entropy quantifies the system's modular structure and provides vital insights into internal connectivity and hierarchical organization (Fortunato, 2010). During the conservation phase (K), community entropy typically decreases, reflecting the consolidation of organizational structures.

While powerful, entropy measures also come with some significant limitations. They are sensitive to network size, which requires careful normalization (Dehmer and Mowshowitz, 2011; Mowshowitz and Dehmer, 2012). Additionally, interpreting entropy values requires considering the specific context of the system being analyzed (Estrada and Knight, 2015), and it is ideal to use these metrics alongside others for a comprehensive understanding of the system (Newman, 2018).

Entropy metrics in complex network analysis represent a fundamental innovation beyond traditional topological metrics' limitations. Unlike conventional measures that provide a one-dimensional view of network structure, entropy metrics offer a multidimensional perspective on system organization, capturing nuances and patterns that would otherwise remain hidden (Bianconi, 2018; Newman, 2003).

With these unique advantages, entropy metrics open up new ways to understand network structures beyond what traditional measures can capture. Instead of offering a flat, one-dimensional view, they provide a more prosperous, multi-layered picture of how networks are organized, allowing us to see subtle patterns and connections that would otherwise stay hidden. In the next section, we'll explore four key entropy metrics that form the backbone of our analysis. Each metric sheds light on different aspects of network structure and dynamics, helping us better understand how complex systems are organized and adapt over time.

2.3. *Entropy metrics for network analysis*

In this study, entropy metrics are calculated using a base-2 logarithm, following the original framework established by Shannon (1948). This choice aligns with the theoretical underpinnings of information theory, where entropy is interpreted in terms of binary information units (bits). While alternative logarithmic bases, such as the natural logarithm (ln), are frequently used in ecology and archaeology to connect entropy with diversity indices (e.g., Chao and Chiu, 2016; Gheorghiade et al., 2023; Jost, 2006), the base-2 logarithm provides a direct link to Shannon's formulation and ensures consistency in interpreting network metrics within the context of information theory. Furthermore, the choice of base primarily affects the scale of entropy values rather than the observed patterns, ensuring the robustness of comparative analyses across networks.

Four fundamental entropy metrics form the core of our analytical framework.

2.3.1. *Degree entropy*

The degree of entropy (H), rooted in Shannon's information theory (Shannon, 1948), represents a fundamental metric for quantifying the heterogeneity of connection patterns within a network. Mathematically expressed in (1):

$$H = -\sum \left(p(k) log_2\, p(k)\right) \tag{1}$$

where $p(k)$ represents the probability of a node having degree k in the network; this measure evaluates the diversity in node connectivity by analyzing the distribution of node degrees throughout the network (Newman, 2018). When calculated, the degree entropy provides crucial insights into the structural organization of the network: higher values indicate greater diversity in connectivity patterns, suggesting a more heterogeneous network structure. In comparison, lower values point to more uniform or regular connection patterns (Bianconi, 2009).

The significance of degree entropy extends beyond mere structural description. In network analysis, it serves as a robust indicator of network stability and resilience (Costa et al., 2007). Networks exhibiting higher degree of entropy typically demonstrate enhanced structural stability and improved resistance to random perturbations (Wang et al., 2006). This characteristic makes degree entropy particularly valuable for analyzing complex social systems, where understanding structural robustness is crucial for evaluating system resilience (Dehmer and Mowshowitz, 2011), and to detect meaningful patterns in network organization (Estrada, 2012).

2.3.2. *Eigenvector entropy*

The eigenvector entropy (H_e) provides a measure for analyzing hierarchical structure in networks, building on fundamental concepts from spectral graph theory (Newman, 2018). Mathematically expressed as in (2).

$$H_e = -\sum \left(\lambda_i\, log_2 \lambda_i\right) \tag{2}$$

where λ_i represents the normalized eigenvalues of the network's adjacency matrix (Schwengber et al., 2021; Wihler et al., 2012). This metric quantifies the distribution of structural importance across the network (Estrada 2011). While eigenvector centrality has been extensively used in archaeological network analysis (Brughmans and Peeples, 2023), applying eigenvector entropy specifically represents a novel approach in archaeological contexts.

In network analysis applications, eigenvector entropy is a tool for understanding hierarchical organization and influence distribution. High values typically indicate a more distributed power structure with multiple centers of influence, while lower values suggest more centralized organizational patterns (Borgatti and Everett, 2006). The metric's potential to capture direct and indirect relationships makes it particularly relevant for archaeological network analysis, where complete interaction patterns are rarely observable (Borgatti and Everett, 2006; Estrada and Knight, 2015).

2.3.3. *Community entropy*

Community entropy (H_c) quantifies the uncertainty in the distribution of community sizes in the network. Mathematically expressed as in (3):

$$H_c = -\sum \left(p_c \log_2 p_c\right) \tag{3}$$

where p_c represents the proportion of nodes belonging to community c (normalized community size), the measure is normalized by the theoretical maximum entropy to allow comparison across networks of different sizes. This metric proves crucial for evaluating the clarity of community structure and assessing the degree of modularity within the system (Fortunato, 2010). Higher values indicate more diverse community distributions, while lower values suggest more clearly defined, distinct community structures (Bianconi, 2018; Zhao et al., 2011).

While community detection methods have been widely applied in archaeological networks to identify social groups and interaction patterns (Brughmans and Peeples, 2023; Mills et al., 2013), community entropy helps quantify the degree of modularity and organization.

The relationship between community entropy and a system's structural organization makes it particularly interesting for studying social network evolution (Schaub et al., 2017), though its application to archaeological data requires careful consideration of the fragmentary nature of the archaeological record.

2.3.4. *Betweenness entropy*

Betweenness entropy (H_b) examines the distribution of intermediation roles within the network. Mathematically expressed as (4):

$$H_b = -\sum \left(p_b\, log_2 p_b\right) \tag{4}$$

where p_b represents the normalized betweenness probability for each node (L. Freeman, 1977; L. C. Freeman et al., 1991). This implementation includes numerical stability measures and normalization procedures to ensure consistent results across different network sizes. This metric proves essential for identifying critical control points in the network and evaluating the distribution of intermediation power (Tutzauer, 2007), particularly useful in identifying key actors in communication networks (Shetty and Adibi, 2005).

The integration of these four entropy metrics provides a comprehensive characterization of network structure, enabling sophisticated analysis of resilience, temporal evolution, and anomaly detection. Combined degree and betweenness entropies allow evaluation of system robustness against perturbations (Krioukov et al., 2012), while changes in entropic metrics can indicate phase transitions in system organization (Castellano et al., 2009). In the specific context of adaptive cycles, these metrics provide fundamental quantitative indicators of potential, connectivity, and resilience, enabling a more precise and complete characterization of adaptive cycle phases than traditional topological metrics alone.

2.4. Phase identification framework

To understand adaptive cycle dynamics in complex networks—such as phases of exploration, exploitation, reorganization, and conservation—we need advanced metrics that reveal aspects like structure, stability, and resilience. Our framework tests the hypothesis that these adaptive cycle phases can be quantitatively identified through the integration of multiple entropy-based metrics, each capturing different aspects of network organization. We expect exploitation phases (r) to show high potential with low resilience values, while conservation phases (K) should display an inverse pattern. Release phases (Ω) should exhibit decreasing values across metrics, and reorganization phases (α) should show increasing potential with variable resilience measures.

Our framework, called PANARCH (Phase Analysis of Network Adaptive Research & Complex Hierarchies), integrates four entropy metrics that capture different aspects of network organization: degree entropy for connectivity patterns, eigenvector entropy for hierarchical structure, community entropy for modular organization, and betweenness entropy for information flow. This combination should provide distinct quantitative signatures for each adaptive cycle phase, allowing for objective identification of phase transitions and system states. This methodological approach will be tested against previously identified homogeneity-fragmentation phases in arrowhead networks from Eastern Iberia (Jiménez-Puerto, 2024), offering an opportunity to validate our entropy-based framework against previously analyzed archaeological patterns.

The analysis is structured through three interrelated dimensions: potential quantification, connectivity measurement, and resilience assessment. Each dimension employs specific combinations of entropy metrics calibrated to detect the hypothesized phase signatures, providing a reproducible method for analyzing complex social system dynamics.

2.4.1. Potential quantification

To start, we analyze the system's potential—its capacity for future growth and development. This is achieved by calculating a weighted combination of key network metrics, including structural diversity (degree entropy), evolutionary capacity (eigenvector centrality entropy), resource availability (clustering and density), and growth potential (inverse density) (Costa et al., 2007). Each metric is normalized for network size and entropy, allowing fair comparison across different types of networks.

In this framework, the degree entropy is calculated using a weighted distribution that considers the degree distribution of the network's nodes, reflecting structural diversity (Wu et al., 2013). Additionally, the eigenvector entropy captures the network's capacity for evolution, based on the centrality of its nodes. The clustering coefficient, adjusted by network density, is used to measure resource availability, while the growth potential is inversely related to the network's overall density (Boccaletti et al., 2006). The final potential value is obtained by combining these normalized components, weighted according to the network size and its inherent characteristics (Newman, 2012). The detailed mathematical formulations and specific analyses for potential quantification are provided in the Supplementary Material, Section S1.2.

2.4.2. Connectivity measurement

Next, we assess network connectivity. This reflects how cohesive, efficient, robust, and centralized the system is. This is a crucial measure of network resilience, as higher connectivity typically correlates with greater robustness against disruptions (Albert et al., 2000).

To calculate connectivity, we use a blend of metrics: modularity, community entropy, and betweenness entropy. Modularity measures the degree to which the network's nodes can be divided into distinct communities, while community entropy quantifies the uncertainty in the network's modular structure (Fortunato, 2010). Betweenness entropy, which reflects the distribution of shortest paths in the network, is also included to assess the robustness of the network's connectivity (L. Freeman, 1977).

In large networks, the global efficiency and degree centralization are incorporated into the connectivity measure. Global efficiency provides insight into the network's overall ability to transmit information, while degree centralization assesses the dominance of individual nodes in terms of their connections (Latora and Marchiori, 2001). These components are combined with adaptive weights that adjust for network size, ensuring that connectivity is measured in a way that is consistent across networks of varying scale. The detailed mathematical formulations and specific analyses for potential quantification are provided in the Supplementary Material, Section S1.3.

2.4.3. Resilience assessment

Resilience here means the network's ability to handle disruptions and bounce back. The resilience measure is constructed from several key components: structural redundancy, role diversity, modularity, and local stability. Structural redundancy is quantified using betweenness entropy, which captures the network's robustness regarding its shortest paths (Kharrazi et al., 2020). Role diversity, calculated through the participation coefficient, measures the diversity of nodes' roles within the network's communities, which is critical for ensuring resilience. Modularity and community entropy are again used to assess the network's balance and stability, while local stability is derived from the clustering coefficient and density metrics.

We calculate resilience by combining these metrics with weights that adapt to the network's size and structure. These weights ensure that the resilience calculation reflects the varying importance of each component depending on the specific characteristics of the network (Goh et al., 2001). The final resilience score is normalized, ensuring it falls within a defined range that allows for meaningful comparisons between networks of different sizes and structures. The complete methodological details for resilience assessment, including all formulas and analysis procedures, can be found in the Supplementary Material, Section S1.4.

2.4.4. Adaptive cycle phases recognition

After integrating the metrics for potential, connectivity, and resilience, we can classify the network's state into one of the four adaptive cycle phases: release (Ω), exploitation (r), reorganization (α), and conservation (K). These phases are identified by examining not only the relative order of the three composite metrics at each time step (Holling, 2001) but also by considering the direction of change and a state-machine sequence that enforces the canonical progression α - > r - > K -> Ω -> α. This ensures that the phase transitions follow the typical adaptive cycle logic rather than jumping arbitrarily from one phase to another.

Our approach combines ratios-based analysis and state machine logic. In each time step, we calculate three main composite metrics: P (Potential), C (Connectedness), and R (Resilience). For the dominance analysis, we define relative ratios of each metric as:

$$p_{rel} = P \,/\, (P + C + R)$$

$$c_{rel} = C \,/\, (P + C + R)$$

$$r_{rel} = R \,/\, (P + C + R)$$

Each ratio lies in the interval [0,1], and $p_{rel} + c_{rel} + r_{rel} = 1$. We then identify which metric dominates by determining which relative ratio is largest.

To capture the direction of change, we compare each metric at the current step to its previous value. For instance, for potential:

p-change = $(P_{current} - P_{previous}) / (|P_{previous}| + \varepsilon)$

where ε (a small constant, e.g., 10-9) avoids division by zero. The same calculation applies for c change and r change.

Based on metric dominance and changes, we assign a tentative phase following specific rules:

If C dominates and $\Delta R < 0$ (resilience is decreasing), we assign Release (Ω)

If R dominates and $\Delta P > 0$ (potential is increasing), we assign Reorganization (α)

If C dominates and ($\Delta P > 0$ or $\Delta C > 0$), we assign Exploitation (r)

Otherwise, we assign Conservation (K)

These rules, whose flowchart can be seen in Fig. 2, align with adaptive cycle interpretations: Exploitation reflects growth in connectivity or potential, Release indicates dropping resilience, Reorganization involves rising potential under dominant resilience, and Conservation serves as the stable fallback phase.

After the tentative assignment, we employ a state machine approach to enforce the canonical cycle α - > r - > K -> Ω -> α. This prevents illogical transitions - for example, if the previous phase was Exploitation (r), we don't allow a direct jump to Reorganization (α), instead requiring movement through Conservation (K). At the very first step (step = 0), with no previous phase, we compute initial (P, C, R) ratios and make a direct phase assignment. In subsequent steps, we calculate new metrics, assess changes, assign a tentative phase, and apply state machine rules to ensure valid transitions.

Within PANARHC framework, each step draws on entropy-based metrics (e.g., degree entropy, eigenvector entropy, modularity) to determine the numerical values of P, C, and R. The adaptive cycle logic then determines the system's phase by examining relative ratios (prel, crel, rrel), directional changes (ΔP, ΔC, ΔR), and the canonical ordering.

This combined method - entropy metrics plus ratios-based adaptive cycle - provides a rigorous, reproducible framework for analyzing complex network dynamics.

By focusing on comparative dominance, we avoid the pitfalls of fixed thresholds, allowing the model to adapt dynamically to varying scales and intensities in different network states. This aligns with recent work on relative dominance approaches in adaptive cycles, where the interplay between metrics is emphasized over strict quantifications (Gunderson and Holling, 2002; Holling, 2001). Moreover, this approach aligns with of ecological resilience (Allen et al., 2014; B. Walker and Salt, 2012). This methodology supports the identification of subtle shifts that could signify a phase transition, helping to capture complex system dynamics more accurately, and its comparative logic aligns with

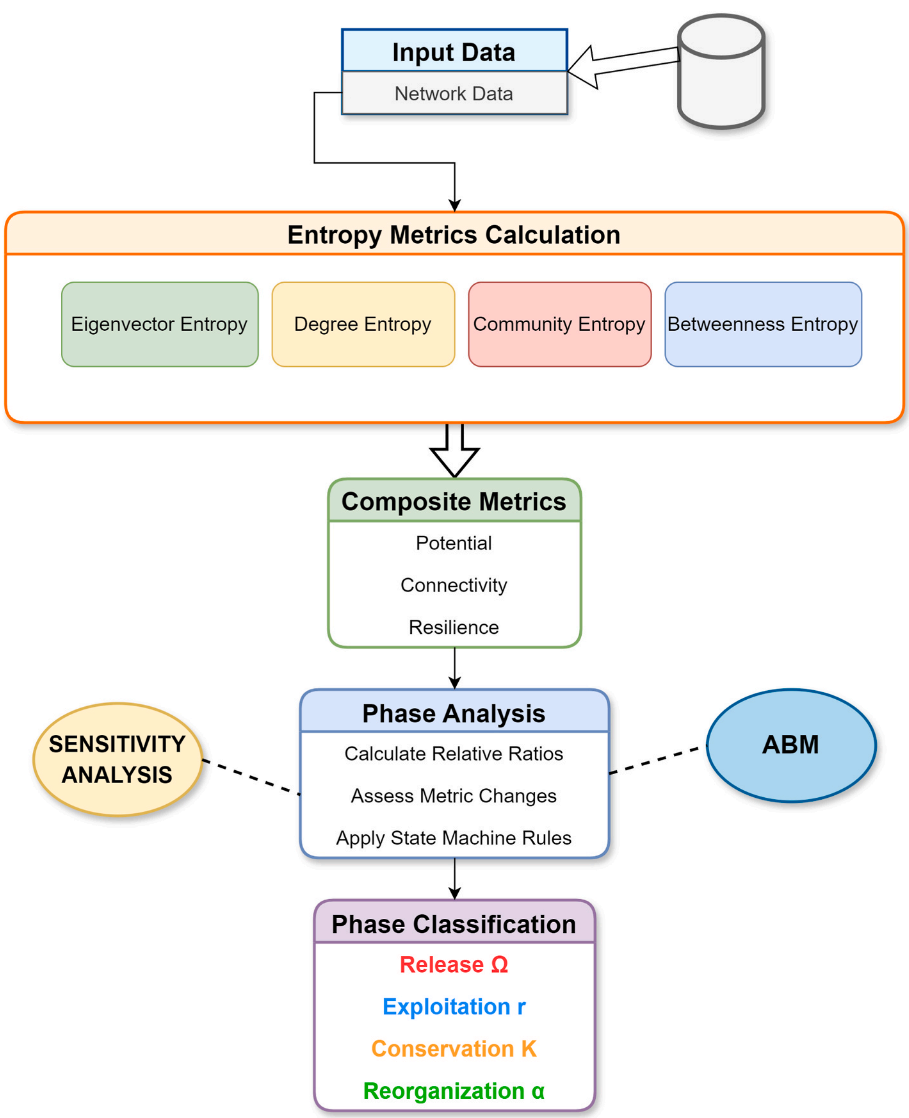

Fig. 2. PANARCH flowchart.

adaptive cycle theory.

This approach aligns with recent work on adaptive cycles, where phase transitions are understood as shifts in directional patterns rather than strict values. The model is further strengthened by memory-based phase transitions. This trend-based approach has been recognized in studies of ecological resilience, where transitions are understood as shifts in directional patterns rather than strict values, enabling the model to respond flexibly to both gradual and sudden changes without imposing hard cutoffs. The approach is further strengthened by memory-based phase transitions, well-supported by adaptive cycle theory (Allen et al., 2014; Biggs et al., 2015; Gunderson and Holling, 2002), which suggests that each phase tends to build conditions that facilitate the next. Recent studies on complex systems have reinforced this perspective, demonstrating how feedback and continuity play crucial roles in phase dynamics.

This integrated methodological approach combines entropy-based analysis, relative dominance metrics, and canonical transition rules, offering multiple advantages: objectivity through precise entropy calculations, multidimensionality by combining indicators that capture structural diversity and centralization, and consistency by enforcing logical cycle transitions. By focusing on comparative patterns rather than strict thresholds, the model maintains the flexibility needed to adapt to different scales and capture both gradual changes and abrupt transitions in complex systems, responding to the inherent dynamics of adaptive cycles.

To accomplish this analysis, a Python script was developed to handle data comprehensively, generating detailed reports and visualizations based on calculated metrics. PANARCH script integrates several essential libraries that facilitate data processing and visualization. For instance, NetworkX (Hagberg et al., 2005) was employed to construct and analyze network structures, allowing for the calculation of entropy and other network metrics essential for adaptive cycle analysis. NumPy (Harris et al., 2020) provided support for numerical computations, optimizing operations on large datasets. Pandas (McKinney, 2010) enabled structured data handling and manipulation, making organizing and analyzing network-related data easier across different phases of the adaptive cycle.

For visual representation, Matplotlib (Hunter, 2007) was used to create static graphs, while Plotly (Plotly Technologies Inc, 2015) enabled interactive visualizations in html format (Supplementary Material), allowing for a deeper exploration of network behaviors and trends. Additionally, SciPy (Virtanen et al., 2020) was used to conduct advanced signal processing tasks, such as identifying peaks in network connectivity and resilience data, which were essential for pinpointing phase transitions. The DBSCAN clustering algorithm from Scikit-Learn (Pedregosa, 2011) allowed clusters within the network data to be identified, giving further insight into community structures and network resilience.

These tools collectively provide a robust analytical framework where each library contributes specific functionalities to the script, making the data processing workflow efficient and the results easily interpretable through reports and graphical outputs. This approach facilitates an in-depth exploration of adaptive cycle dynamics in complex network analysis.

2.4.5. Sensitivity analysis, reproducibility and ABM

To ensure methodological rigor and validate our approach, we conducted extensive statistical testing alongside our sensitivity analysis and agent-based modeling. Initial data exploration with Shapiro-Wilk tests revealed non-normal distributions ($p < 0.05$), and Levene's tests confirmed heteroscedasticity across metrics. Consequently, we primarily relied on non-parametric methods (Kruskal-Wallis and Dunn's tests) for phase comparisons, while also conducting exploratory parametric analyses to provide complementary perspectives on effect magnitudes. This dual approach revealed consistent, significant differences between phases across all testing methodologies (all $p < 0.001$), underscoring the robust differentiation between adaptive cycle phases. A comprehensive explanation of statistical procedures, including detailed justification for methodological choices, is provided in Supplementary Material, Section 5.1.

To ensure the robustness and reproducibility of our phase recognition approach, we implemented an advanced sensitivity analysis framework and an agent-based model (ABM) that incorporates stationarity and ergodicity analyses (Borgonovo et al., 2022; Ligmann-Zielinska et al., 2020; Thiele et al., 2014).

The sensitivity analysis evaluates how different weight combinations influence phase identification by systematically exploring an extended parameter space. This space includes diverse combinations of weights for diversity, evolution, resources, and growth. These weights are applied to basic network metrics, such as density and average clustering, to compute composite measures of potential, connectedness, and resilience. We employed a refined weight generation method using both grid-based and random sampling approaches to ensure extensive coverage of the parameter space.

The sensitivity framework performs statistical evaluations including normality tests (Shapiro-Wilk) (Shapiro and Wilk, 1965), homoscedasticity assessments (Levene's test) (Zimmerman, 2004), and comparisons across groups using both parametric (ANOVA, Tukey HSD) (Fisher, 1992; Tukey, 1949) and non-parametric methods (Kruskal-Wallis, Mann-Whitney *U* test with Bonferroni correction, Dunn's test)(Dunn, 1964; Kruskal and Wallis, 1952; Mann and Whitney, 1947). Additional statistical evaluations include Spearman correlations (Spearman, 1961) for analyzing relationships between metrics, logistic regression with cross-validation (Cox, 1958), bootstrap analysis (Efron and Tibshirani, 1993), and stability assessments through Jensen-Shannon divergences (Lin, 1991) measure stability across phase distributions and Kolmogorov-Smirnov tests (Massey, 1951). These statistical analyses are complemented by visualizations including heatmaps, phase transition diagrams, and metric-versus-phase distributions to support comprehensive examination of relationships between network metrics and adaptive cycle phases. Visualizations such as heatmaps, phase transition diagrams, and metric-versus-phase distributions support a comprehensive understanding of the relationships between network metrics and adaptive cycle phases.

Reproducibility is further enhanced through the integration of an agent-based model. The ABM simulates network evolution using agents that interact dynamically, incorporating mechanisms such as rewiring, mutation, and influence thresholds. Key parameters include connection thresholds, mutation probabilities, and rewiring probabilities. The model tracks both individual agent states and emergent network properties, enabling the detection of phase transitions. The ABM extends its analysis to include stationarity and ergodicity evaluations. Stationarity is assessed using the Augmented Dickey-Fuller (ADF) and KPSS tests (Kwiatkowski et al., 1992; Said and Dickey, 1984), while ergodicity is examined by comparing time and ensemble averages across multiple simulations. Metrics such as ergodicity ratios and distribution stability measures (e.g., Kolmogorov-Smirnov and Jensen-Shannon tests) (Massey, 1951) ensure robust validation of phase identification under diverse dynamic conditions.

Our structured visualization approach includes phase distribution analyses, weight combination heatmaps, and phase transition maps, alongside additional 3D trajectory plots and phase timelines. These visualizations provide nuanced insights into both static and dynamic properties of the network, illustrating the robustness and adaptability of our phase recognition methodology. The dual implementation of sensitivity analysis and ABM provides a rigorous framework for validating phase detection across a wide range of scenarios and parameter configurations, ensuring the stability, reproducibility, and robustness of our results. The complete detailed results of all statistical tests and their implications can be found in the supplementary material, where we provide comprehensive information about the methodology's validation. We now turn our attention to PANARCH's application to archaeological networks, demonstrating its practical utility in understanding social dynamics.

3. Case study: arrowhead networks in Eastern Iberia

To validate our methodological framework and demonstrate its practical applications, we examine a case study focusing on the evolution of social networks during the transition from Late Neolithic to Early Bronze Age in Eastern Iberia (5300-3800 cal BP). This analysis employs flint arrowheads as proxies for social interaction and information transmission that have already been published (Jiménez-Puerto, 2024), leveraging their well-documented chronological and typological variations to trace changes in social connectivity and cultural dynamics. This works is following the line proposed by previous works in the field, relying on the solid base proposed by them (Brughmans, 2013, 2014; Brughmans and Peeples, 2023; Collar et al., 2015; Knappett, 2011; Peeples, 2019). The dataset and the associated analysis tools are available in ZENODO public repository (see Supplementary Materials). The data was processed using.graphml files, which contain network information similar to lithic arrowheads, structured in discrete time windows of 150 years each. These.graphml files enable us to analyze and visualize the evolution of arrowhead similarity networks across different temporal segments, providing insights into changing patterns of cultural transmission and social interaction throughout this critical transition period.

3.1. Archaeological context and data

The study area encompasses the Mediterranean façade of the Iberian Peninsula, specifically the hydrographic basins of the Júcar, Segura, Almanzora-Andarax, and the Ebro tributaries (Guadalope, Martín, and Cérvol). This region, corresponding mainly to the modern provinces of Castellón, Valencia, Alicante, Murcia, Almería, Albacete, Cuenca, and Teruel, presents a natural laboratory for studying cultural transitions, with the Júcar River, traditionally considered a significant cultural boundary (Gil-Mascarell, 1995; Tarradell, 1965).

The chronological framework spans from 5300 to 3800 cal BP, encompassing four distinct cultural periods: Late Neolithic (5300-4800 cal BP), Pre-Bell Beaker Copper Age (4800-4550 cal BP), Bell Beaker phase (4550-4200 cal BP), Early Bronze Age (4200-3800 cal BP).

This timeframe coincides with significant environmental changes, including an aridification trend beginning around 5300 cal BP and culminating in the 4.2k event (Brisset et al., 2020). Demographic models for this period suggest an unstable panorama fitting a nearly logistic growth pattern, with three notable turning points: a rapid increase after 5300 cal BP, followed by stabilization; a sharp rise around 4800 cal BP, followed by a slight decline between 4500 and 4200 cal BP; and a period of sustained growth during the transition to the Bronze Age (4300-3850 cal BP) (Bernabeu et al., 2018).

Our analysis employs a typology of seven distinct arrowhead forms (Jiménez-Puerto, 2024): rhomboid or rhombus eye, cruciform or with side appendages, leaf-like, peduncled without barbs, concave base, Asymmetric, and Barbed-tanged. These types show apparent spatial and temporal distributions, making them ideal markers for studying information transmission patterns. Concave base and asymmetric points are primarily concentrated south of the Júcar River, associated with the Los Millares culture. In contrast, pedunculated and finned points show a more uniform distribution across all sub-basins, with a chronological focus in the second half of the considered period. Cruciform, leaf-like, and rhomboid points, potentially older chronologically, also show wide geographic distribution (see Fig. 3).

This case study analyzes archaeological arrowhead assemblages from systematically excavated sites across the Mediterranean façade of the Iberian Peninsula, supplemented with data from neighboring provinces (Madrid, Zaragoza, Tarragona, and Granada) to avoid artificial boundaries. The dataset has been compiled following strict protocols to ensure data comparability and reliability, with information extracted from published monographs, compendia, and articles. The typological classification follows established criteria, providing a robust foundation for analyzing social interactions through material culture similarities. Nevertheless, the typological framework employed in this study draws upon but diverges from the classification system proposed by Juan-Cabanilles (2008). While his contributions remain a foundational reference for the typology of arrowheads in Eastern Iberia, our approach incorporates modifications published by recent works about lithic arrowheads in the late Neolithic (e.g., Armero et al., 2020, 2021; Pardo-Gordó et al., 2022). These adjustments aim to account for regional and chronological variability identified in subsequent research and to align the classification with the specific analytical goals of this study. A detailed discussion of these criteria and filtering processes is available in the supplementary material, providing transparency and fostering reproducibility of our methodology.

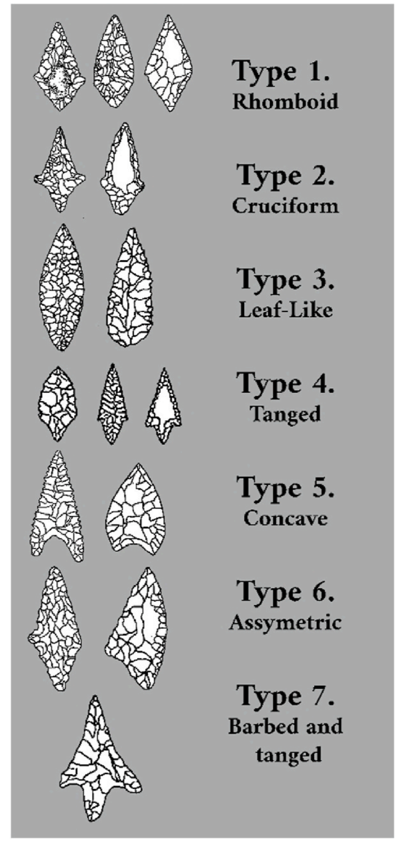

Fig. 3. Types of arrowheads employed in the analysis.

The archaeological record is inherently fragmented and chaotic due to taphonomic processes, post-depositional disturbances, and research biases (Bailey, 2007; Perreault, 2019; Surovell et al., 2009; Bailey, 2007; Surovell et al., 2009; Perreault, 2019). These formation processes significantly impact our ability to interpret past human behaviors and social dynamics. Therefore, the data collection methodology prioritizes systematic excavations and well-documented archaeological contexts, creating a reliable framework for studying information flow and social connectivity patterns during a crucial period of prehistory. Special attention is given to the differential distribution patterns north and south of the Júcar River boundary, as this geographical feature has been traditionally considered a significant cultural frontier (Bernabeu et al., 2018).

This table (see Table 1) provides a concise summary of the data, which forms the foundation for studying the evolution of social networks and information transmission patterns during this transitional period in Eastern Iberia. It summarizes the data, highlighting the

Table 1
Data summary.

Chronological Period	*Time Frame (cal BP)*	*Nº of Sites*	*Dens. of Arrowheads*	*Arrowhead Types*
Late Neolithic	5300–4800	40	High	Rhomboid, Cruciform, Leaf-like
Copper Age (Pre-Bell-Beaker)	4800–4550	63	Very High	Peduncled, Barbed, Concave base
Copper Age (Bell-Beaker)	4550–4200	32	Moderate	Peduncled, Finned
Early Bronze Age	4200–3800	21	Low	Finned, Asymmetric

distribution of sites, the density of arrowhead artifacts, and the dominant morphological types associated with each chronological period. The table also underscores the variability in artifact density and type distribution, reflecting broader patterns of information transmission and social connectivity in Eastern Iberia.

4. Results

Our results are presented in two main blocks. First, we establish the methodological foundations through complementary validation approaches: a comprehensive sensitivity analysis of the entropy-based metrics and an Agent-Based Model (ABM) implementation. This dual validation strategy allows us to assess both the robustness of our phase quantification method and its behavior under controlled conditions. Following this methodological validation, we present the application of our framework PANARCH to analyze the evolutionary dynamics of arrowhead similarity networks in Eastern Iberia during the Late Neolithic to Early Bronze Age transition.

4.1. Sensitivity analysis, reproducibility and ABM results

To validate our entropy-based approach to phase quantification, we conducted two complementary analyses. First, a sensitivity analysis examined the robustness of our metrics across a wide range of parameter combinations, allowing us to assess the stability and reproducibility of phase identification. Second, we developed an Agent-Based Model to test our quantification method under controlled conditions, simulating system dynamics that should theoretically align with adaptive cycle behavior. The results of both approaches provide insights into the strengths and limitations of our phase quantification methodology.

4.1.1. Sensitivity and phase analysis results

Our sensitivity analysis encompassed 10,840 iterations across different weight combinations for diversity, evolution, resources, and growth parameters. The analysis revealed distinct patterns in phase distribution and system dynamics. While comprehensive statistical validation of our method is provided in the supplementary material, we now focus on the main trends observed in the results.

The phase distribution analysis showed Reorganization (α) as the most frequent phase (32 % of cases), followed by Conservation (K) (30 %), Release (Ω) (20 %), and Exploitation (r) (17 %). A chi-square test confirmed statistically significant differences in phase frequencies ($p < 0.001$). This distribution suggests a system tendency toward reorganization and conservation states (see Fig. 4, D).

Metric analysis revealed characteristic patterns across phases. Potential (P) showed highest values during Conservation (median ~0.45, $\sigma = 0.12$) and Reorganization (median ~0.35, $\sigma = 0.14$) phases (Fig. 4, A). Connectedness (C) peaked during Release and Exploitation phases (medians ~0.5, $\sigma = 0.15$), while showing lower values during Conservation and Reorganization (medians ~0.25, $\sigma = 0.11$) (Fig. 4, C). Resilience (R) demonstrated maximum values during Reorganization (median ~0.15, $\sigma = 0.08$), with minimal values during Release (median ~0.05, $\sigma = 0.04$) (Fig. 4, B).

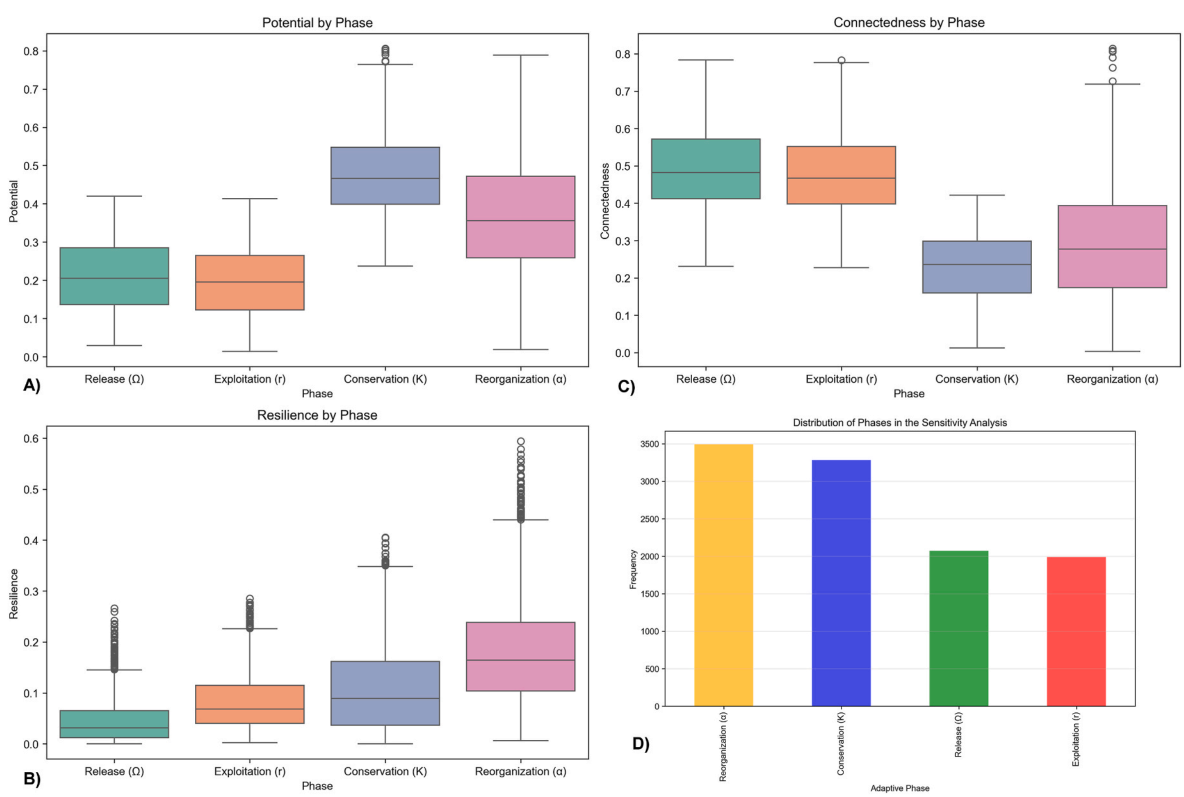

Fig. 4. Phase characteristics in the sensitivity analysis: A) Potential by phase; B) Resilience by phase; C) Connectedness by phase; D) Distribution of phases in the sensitivity analysis.

The transition analysis identified key pathways in the system's evolution. The strongest transitions occurred from Conservation to Release (1332 transitions, 31 %), followed by Release to Reorganization (1095 transitions, 28 %), Conservation to Exploitation (751 transitions, 19 %), and Exploitation to Reorganization (467 transitions, 12 %). Self-loops were present in all phases, indicating phase persistence under certain conditions.

Statistical validation of these patterns was performed using multiple tests, including Shapiro-Wilk for normality, Levene for homoscedasticity, and ANOVA and Kruskal-Wallis for group comparisons, ensuring the robustness of our findings. Mann-Whitney U tests revealed significant differences in most phase comparisons ($p < 0.05$), with notable exceptions like Release vs. Exploitation in connectedness ($p = 0.322$). These non-parametric results were consistent with the parametric approaches, confirming distinct phase characteristics even under less restrictive statistical assumptions. Further analysis revealed significant correlations between metrics, with a strong negative correlation between potential and connectedness ($\rho = -0.843$), moderate negative correlation between connectedness and resilience ($\rho = -0.530$), and weak positive correlation between potential and resilience ($\rho = 0.268$). Bootstrap analysis (1000 iterations) demonstrated consistent phase identification (Cohen's $\kappa = 0.82$), and repeated simulations using different random seeds preserved the statistical significance of observed transitions ($p < 0.001$).

Logistic regression analysis with cross-validation achieved a consistent accuracy of ~0.60 across folds, with coefficients highlighting the importance of resilience in distinguishing Reorganization (9.39) and Conservation (−9.99) phases, connectedness in characterizing Release phase (−6.92), and potential showing moderate effects across all phases. These regression results further support the discriminatory power of our metrics in phase identification.

The results of our sensitivity analysis provide strong evidence supporting the reliability of entropy-based metrics for quantifying adaptive cycle phases. The observed phase distribution aligns with theoretical expectations, showing predominant Conservation and Reorganization phases (62 % combined), while the clear differentiation in metric values across phases demonstrates the system's ability to capture distinct phase characteristics. The transition patterns follow theoretically expected pathways, with the strongest sequence ($K \rightarrow \Omega \rightarrow \alpha \rightarrow r$) matching the adaptive cycle's canonical progression. While these findings suggest that entropy-based metrics effectively capture the fundamental dynamics of adaptive cycles, a comparative analysis with alternative quantification methods, presented in subsequent sections, will provide additional validation of this approach and help establish its relative strengths and limitations in phase identification.

4.1.2. ABM results

The Agent-Based Model (ABM) simulation results demonstrate distinct patterns in system dynamics and phase transitions across 200 time steps. The temporal evolution analysis (Fig. 5, D) reveals remarkable stability in the system's base metrics, with potential maintaining a steady range around 0.37 (±0.01), connectedness stabilizing at approximately 0.45 (±0.005), and resilience showing controlled fluctuations between 0.62 and 0.72. This stability suggests that the ABM effectively maintains system cohesion while allowing for dynamic adjustments within controlled boundaries.

The phase-specific distribution analysis of the three key metrics (Fig. 5A and B and C) reveals distinctive characteristics for each phase of the adaptive cycle. Resilience values show clear phase-specific patterns (Fig. 5, B), with the Conservation (K) phase dominating the higher resilience range (0.67–0.70), Reorganization (α) appearing frequently in the moderate resilience range (0.65–0.68), and Release (Ω) and

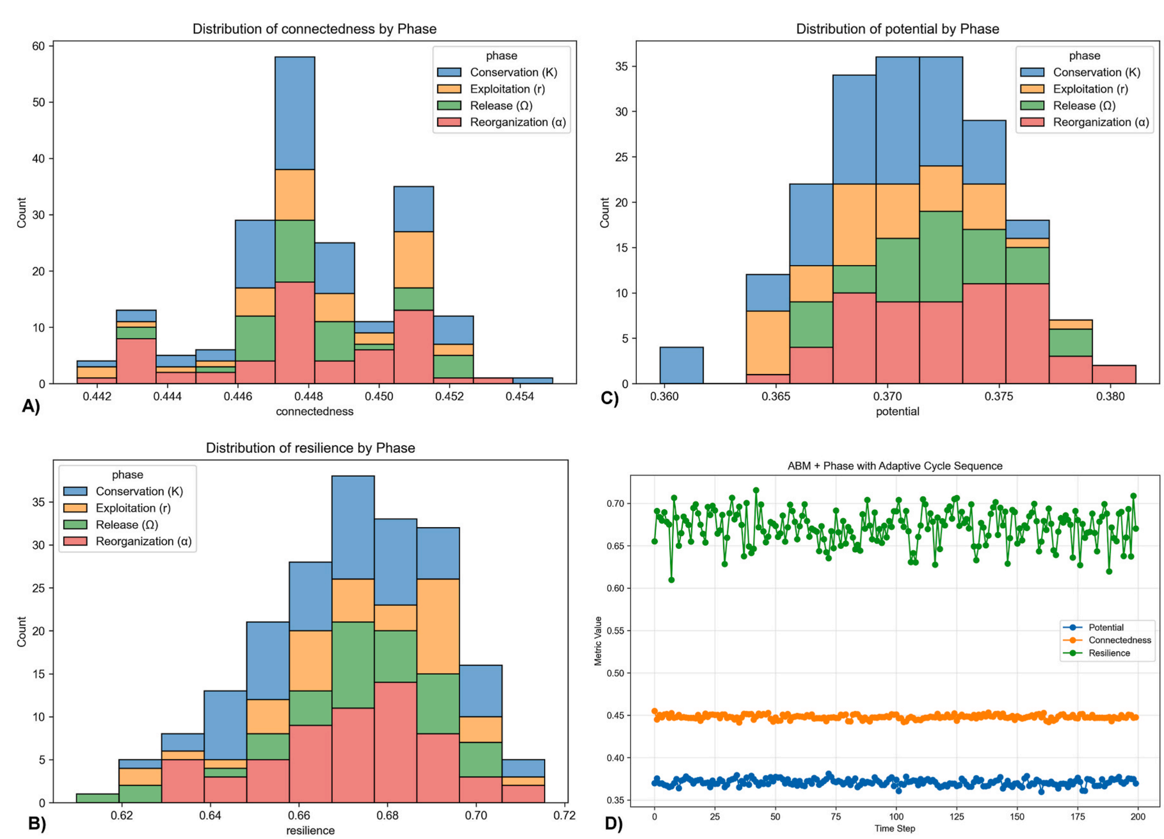

Fig. 5. Phase distribution analysis from ABM simulation: A) Distribution of connectedness by phase; B) Distribution of resilience by phase; C) Distribution of potential by phase; D) Temporal evolution of system metrics in the ABM.

Exploitation (r) phases clustering in the lower resilience ranges (0.62–0.65). The connectedness metric (Fig. 5, A) demonstrates tight clustering, with all phases showing significant overlap in the 0.444–0.452 range, though Conservation (K) exhibits the highest frequency at peak connectedness (0.448), while Exploitation (r) and Release (Ω) phases show more dispersed distributions. Potential values (Fig. 5, C) reveal phase-specific concentrations, with Conservation (K) dominating the 0.370–0.375 range, Reorganization (α) and Exploitation (r) showing similar distributions in the 0.365–0.370 range, and Release (Ω) appearing more frequently in lower potential regions.

These results demonstrate the ABM's ability to maintain system stability while reproducing aspects of adaptive cycle dynamics. While the differentiation of phases through metric distributions suggests that the model captures some transitional characteristics, the constrained metric ranges indicate that further refinement may be needed to fully validate the entropy-based approach to phase quantification. The comparison with the previously published quantification system, addressed in subsequent sections, will serve to better understand these limitations and potentially calibrate the model to achieve a more dynamic representation of adaptive cycles while maintaining system persistence.

4.1.3. PANARCH results

Our analysis of the arrowhead similarity networks across ten temporal windows revealed distinctive patterns in network evolution and adaptive cycle dynamics. The study shows a complex trajectory through the adaptive cycle space (see Fig. 6), with clear transitions between different system states that provide insights into the social dynamics of Eastern Iberia during the Late Neolithic to Early Bronze Age transition.

The system exhibits notable variations in its composite metrics throughout the temporal sequence. Potential values range from a minimum of 0.30 (Window 8) to a maximum of 0.38 (Window 2), indicating fluctuating levels of system resources and opportunities. Connectedness shows a general declining trend from initial values around 0.48 (Window 1) to 0.40 (Window 10), suggesting a gradual reduction in system rigidity. Resilience demonstrates the widest variation, from 0.48 (Window 2) to a maximum of 1.00 (Window 8), indicating significant changes in the system's adaptive capacity (see Fig. 6).

Our adaptive cycle analysis identified all four canonical phases

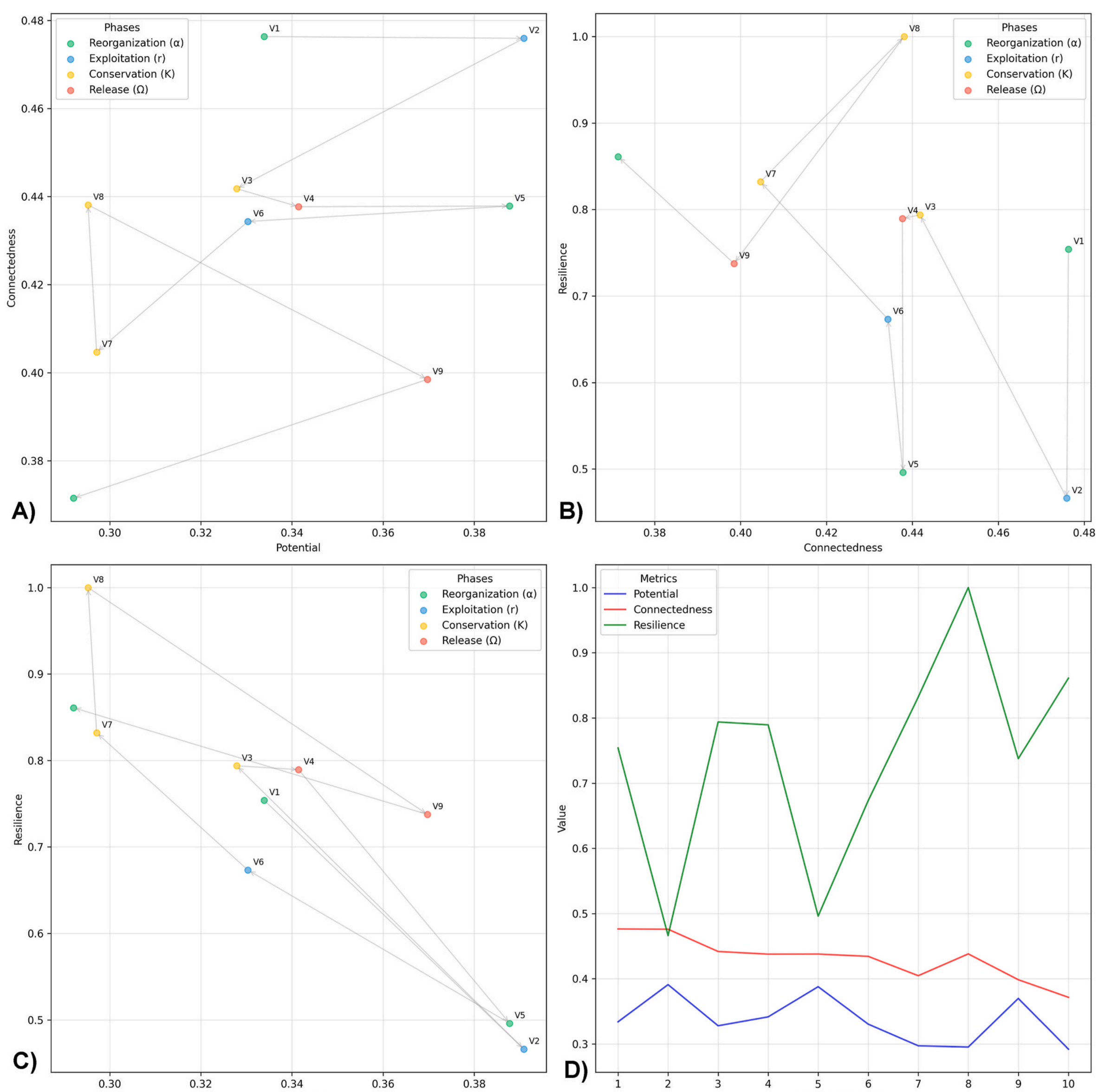

Fig. 6. Two-dimensional projections of key metrics' adaptive cycle trajectory and temporal evolution. A) Potential vs. Connectedness projection. B) Connectedness vs. Resilience projection. C) Potential vs. Resilience projection. D) Temporal evolution of the three key metrics across all windows.

across the temporal sequence (see Fig. 6A and B and C). The analysis reveals clear transitions through the phases. Reorganization (α) appears in Windows 1 and 5, showing resilience levels ranging from 0.75 to 0.50 with increasing potential (0.33–0.38). Exploitation (r) occurs in Windows 2 and 6, characterized by high potential in early stages (0.38) declining in later periods (0.34), with moderate connectedness (averaging 0.44). Conservation (K) is observed in Windows 3, 7, and 8, with the highest resilience values (reaching 1.00 in Window 8). Release (Ω) manifests in Windows 4 and 10, with balanced metrics but declining connectedness (averaging 0.42). This progression through the phases suggests a resilient social system capable of maintaining functionality through regular cycles of reorganization rather than through rigid maintenance of existing structures.

The transition network analysis reveals structured phase changes (see Fig. 7). The most frequent transition is from Conservation (K) to Release (Ω), while Conservation emerges as the most stable phase with three occurrences and one self-loop. Reorganization appears at critical junctures (start and mid-sequence), suggesting its role in system renewal. This structured progression through the phases suggests a resilient social system capable of maintaining functionality through regular cycles of reorganization rather than through rigid maintenance of existing structures.

The temporal evolution of metrics reveals distinct patterns in social organization.

- Potential maintains relative stability (0.295–0.391) throughout the sequence, suggesting consistent resource availability
- Connectedness shows a gradual declining trend (0.476 → 0.398), indicating a shift toward more flexible social structures over time
- Resilience exhibits the most dramatic fluctuations (0.466–1.000), with peaks during Conservation phases suggesting periods of enhanced system stability.

The patterns identified through our quantitative analysis reveal significant implications for understanding social dynamics during this crucial period. The earliest phase of our sequence (Windows 1–2) indicates a highly structured social system, evidenced by peak connectedness values exceeding 0.475. This aligns with archaeological evidence for the Late Neolithic period, suggesting well-established information exchange networks and standardized production practices. The high connectedness values likely reflect strong inter-community relationships and shared technological traditions in arrowhead manufacture.

As the sequence progresses, we observe a significant reorganization period during Windows 5–6, characterized by fluctuating resilience values (0.496–0.673) and moderate connectedness. This transitional phase coincides with the arising of new cultural elements and may represent a period of social experimentation and adaptation. During this time, communities appear to have restructured their interaction networks while maintaining essential functionality, as evidenced by the stable potential values.

The system reaches its maximum stability in Window 8, achieving a remarkable resilience value 1.000, accompanied by moderate connectedness (0.438) and relatively low potential (0.295). This peak in system stability suggests a highly successful adaptation period, where social structures have evolved to balance flexibility and robustness effectively. This timing corresponds with the consolidation of Bronze Age social patterns, indicating that the transition to new social arrangements enhanced rather than compromised system stability.

By the sequence's end, we observe an intriguing pattern where

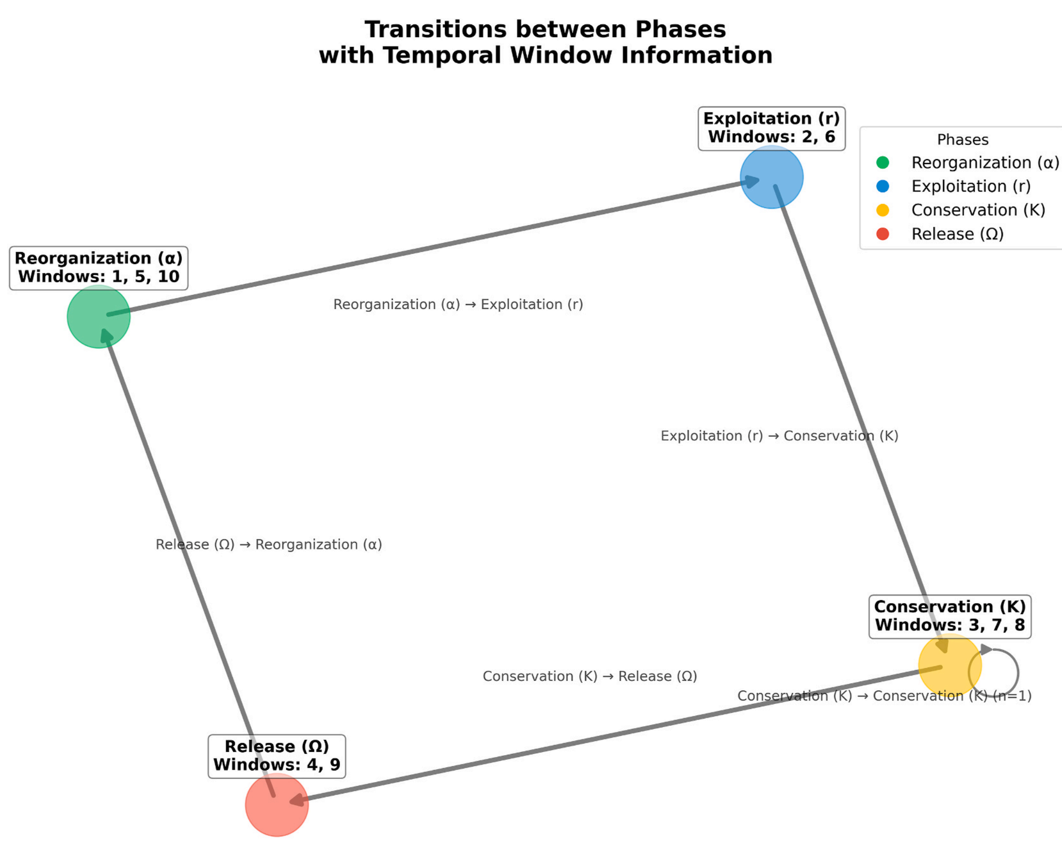

Fig. 7. Network representation of phase transitions showing the sequence of changes between adaptive cycle phases. Node colors represent different phases, node sizes indicate phase frequency, and edges show transition patterns. Labels indicate the temporal windows corresponding to each phase. 3D interactive Transition Phase distribution can be found in Supplementary Material. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

decreased systemic rigidity (connectedness declining to 0.398) does not lead to system instability. Instead, the maintenance of significant resilience values (0.738) suggests the appearance of more flexible yet equally effective social structures. This transformation implies that communities had developed adaptive strategies that allowed for greater local autonomy while maintaining sufficient inter-group connections to ensure system stability. Such a pattern challenges traditional interpretations that might view decreased connectivity as evidence of social breakdown, instead suggesting a sophisticated process of social reorganization that enhances long-term sustainability.

The methodology demonstrates robust phase identification, as evidenced by our comprehensive validation through sensitivity analysis and Agent-Based Model simulations. This validation framework successfully differentiates states and captures logical progression through the adaptive cycle, providing a quantitative foundation for understanding social evolution during the Late Neolithic to Early Bronze Age transition. These results validate the application of adaptive cycle theory to archaeological networks while offering specific insights into the dynamics of social change in Eastern Iberia during this crucial period.

5. Discussion and conclusion

Applying entropy-based network analysis to arrowhead similarity patterns has revealed a sophisticated picture of social transformation during the Late Neolithic to Early Bronze Age transition in Eastern Iberia. Our results demonstrate a social system that successfully navigated significant structural changes while maintaining and even enhancing its adaptive capacity, providing new insights to traditional interpretations of social change during this period.

The temporal evolution of system metrics presents a particularly nuanced view of social transformation. The documented decline in connectedness values, from 0.476 in Window 1 to 0.398 in Window 9, rather than indicating system degradation, appears to reflect a strategic adaptation toward more flexible social arrangements. This interpretation is strengthened by the system's ability to maintain stable potential values (ranging between 0.295 and 0.391) while achieving peak resilience (reaching 1.000 in Window 8). Such patterns suggest that decreased connectivity served as an adaptive strategy rather than a sign of systemic failure.

The phase transition analysis reveals structured patterns of social change. The clear progression through adaptive cycle phases ($\alpha \rightarrow r \rightarrow K \rightarrow \Omega$) indicates that social transformations followed organized pathways rather than chaotic fluctuations. Multiple complete adaptive cycles are particularly significant, suggesting robust mechanisms for managing social change. While these dynamics reflect complex system behavior, the observed patterns are interpreted as deliberate organizational strategies rather than emergent properties arising spontaneously from system interactions. The extended Conservation phase (Windows 7–8), marked by maximum resilience values, coincides with archaeological evidence suggesting a period of cultural consolidation. This timing implies that communities had developed effective strategies for balancing stability and adaptation.

The relationship between our quantitative results and the archaeological record is especially revealing. The high initial connectedness values (in Windows 1–2) align with archaeological evidence for similar production practices and extensive exchange networks characteristic of the Late Neolithic. The subsequent reorganization period coincides with the emergence of regional variations in manufacturing techniques. Most notably, the achievement of maximum resilience in Window 8, despite lower connectedness, suggests successful adaptation to new social arrangements during the Bronze Age transition. This pattern suggests that the development of regional distinctions may have served as an adaptive strategy, allowing for local innovation while maintaining broader system stability.

Our methodological framework demonstrates several advantages over traditional approaches. Integrating multiple entropy metrics provides a comprehensive view of system organization beyond conventional single-metric analyses. The relative dominance method for phase identification is suitable for archaeological data, where absolute values may be less meaningful due to preservation biases. The framework's ability to identify clear phase transitions while accounting for gradual changes makes it especially valuable for studying long-term social transformations.

However, several methodological limitations should be acknowledged. The 150-year temporal windows may obscure short-term changes and rapid transitions, while our focus on a single artifact category (arrowheads) limits our understanding of broader social patterns. Preservation biases in the archaeological record affect network reconstruction, and the assumption of network continuity between temporal windows requires careful consideration. From a methodological perspective, developing more sensitive analytical techniques for detecting short-term phase transitions represents a crucial next step. Such refinements would allow for better identification of rapid social changes that current temporal resolutions might obscure.

The framework's archaeological applications could expand through systematic comparison across different regions and time periods, testing its applicability while potentially revealing common patterns in prehistoric societies' management of change. Incorporating environmental and climatic data would enable more comprehensive analysis of system-environment interactions, while the integration with other material culture categories beyond arrowheads could provide richer perspectives on social interaction patterns.

Theoretical advances should focus on examining the relationship between decreased connectivity and enhanced stability observed in our study, a finding that merits further investigation across different archaeological contexts. The development of early warning indicators for phase transitions and more sophisticated predictive models could enhance our understanding of how prehistoric societies anticipated and responded to change.

In conclusion, our analysis reveals that the transition from Late Neolithic to Early Bronze Age in Eastern Iberia represented a sophisticated process of social adaptation rather than a simple trajectory of growth or decline. Communities maintained system functionality through cyclical reorganization processes that enhanced resilience while reducing systemic rigidity. This quantitative evidence supports a view of prehistoric social change as a dynamic adaptation process, where decreased connectedness could serve as a strategy for maintaining long-term stability. The application of this entropy-based network analysis framework to the Iberian case study demonstrates its potential as an analytical tool for understanding long-term social transformations in prehistoric contexts, while offering a quantitative approach to examining how past societies managed and adapted to change.

CRediT authorship contribution statement

Joaquín Jiménez-Puerto: Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization, Writing – original draft, Software, Investigation, Data curation. **Óscar Trull:** Writing – original draft, Investigation, Writing – review & editing, Validation, Formal analysis. **Eamonn Devlin:** Writing – review & editing, Validation, Methodology, Writing – original draft, Software.

Reproducible results

The Associate Editor for Reproducibility downloaded all materials and could reproduce the results presented by the authors.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Joaquin Jimenez-Puerto reports a relationship with University of

Valencia that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.Óscar Trull reports a relationship with Polytechnic University of Valencia that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.Eamonn Devlin reports a relationship with INN Demokritos Athens that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Open Access funding provided thanks to the CRUE-CSIC agreement with Elsevier.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jas.2025.106329.

Data availability

The data that support the findings of this study are openly available in ZENODO at https://zenodo.org/records/14998922.

References

Albert, R., Jeong, H., Barabási, A.-L., 2000. Error and attack tolerance of complex networks. Nature 406 (6794), 378–382. https://doi.org/10.1038/35019019.

Allen, C.R., Angeler, D.G., Garmestani, A.S., Gunderson, L.H., Holling, C.S., 2014. Panarchy: theory and application. Ecosystems 17 (4), 578–589. https://doi.org/10.1007/s10021-013-9744-2.

Archer, M.S., 1995. Realist Social Theory: the Morphogenetic Approach. Cambridge University Press.

Armero, C., García-Donato, G., Jiménez-Puerto, J., Pardo-Gordó, S., Bernabeu, J., 2020. Bayesian classification for dating archaeological sites via projectile points. https://doi.org/10.48550/ARXIV.2012.00657.

Armero, C., Garcıa-Donato, G., Jiménez-Puerto, J., Pardo-Gordó, S., Bernabeu, J., 2021. A Bayesian naıve Bayes classifier for dating archaeological sites. In: 35th International Workshop on Statistical Modelling, p. 274.

Bailey, G., 2007. Time perspectives, palimpsests and the archaeology of time. J. Anthropol. Archaeol. 26 (2), 198–223. https://doi.org/10.1016/j.jaa.2006.08.002.

Barrett, J., 2012. Agency: a revisionist account. En *Archaeological Theory Today*. Cambridge Univ. Press, pp. 146–166.

Bentley, R.A., Maschner, H.D.G. (Eds.), 2003. Complex Systems and Archaeology. Univ. of Utah Press.

Bernabeu, J., Moreno, A., Barton, C.M., 2012. Complex systems, social networks, and the evolution os social complexity in the east of Spain from the Neolithic to pre-roman times. En *the Prehistory of Iberia: Debating Early Social Stratification and the State*. Routledge, pp. 53–73.

Bernabeu, J., Jiménez-Puerto, J., Escribá, P., Pardo-Gordo, S., 2018. C14 y poblamiento en las comarcas centro-meridionales del País Valenciano (c. 7000-1500 cal BC), 27. Recerques del Museu d'Alcoi, pp. 35–48.

Bianconi, G., 2009. Entropy of network ensembles. Physical Review E 79 (3), 036114. https://doi.org/10.1103/PhysRevE.79.036114.

Bianconi, G., 2018. Multilayer Networks, 1. Oxford University Press. https://doi.org/10.1093/oso/9780198753919.001.0001.

Biggs, R., Schlüter, M., Schoon, M.L., 2015. Principles for Building Resilience: Sustaining Ecosystem Services in social-ecological Systems. Cambridge university press.

Boccaletti, S., Latora, V., Moreno, Y., Chavez, M., Hwang, D., 2006. Complex networks: structure and dynamics. Phys. Rep. 424 (4–5), 175–308. https://doi.org/10.1016/j.physrep.2005.10.009.

Borgatti, S.P., Everett, M.G., 2006. A Graph-theoretic perspective on centrality. Soc. Netw. 28 (4), 466–484. https://doi.org/10.1016/j.socnet.2005.11.005.

Borgonovo, E., Pangallo, M., Rivkin, J., Rizzo, L., Siggelkow, N., 2022. Sensitivity analysis of agent-based models: a new protocol. Comput. Math. Organ. Theor. 28 (1), 52–94. https://doi.org/10.1007/s10588-021-09358-5.

Bourdieu, P., 2020. Outline of a theory of practice. In: En *the New Social Theory Reader*. Routledge, pp. 80–86.

Bradtmöller, M., Grimm, S., Riel-Salvatore, J., 2017. Resilience theory in archaeological practice – an annotated review. Quat. Int. 446, 3–16. https://doi.org/10.1016/j.quaint.2016.10.002.

Brisset, E., Revelles, J., Expósito, I., Bernabeu Aubán, J., Burjachs, F., 2020. Socio-ecological contingencies with climate changes over the prehistory in the Mediterranean Iberia. Quaternary 3 (3), 19. https://doi.org/10.3390/quat3030019.

Brughmans, T., 2013. Thinking through networks: a review of formal network methods in archaeology. J. Archaeol. Method Theor 20 (4). https://doi.org/10.1007/s10816-012-9133-8. Article 4.

Brughmans, T., 2014. The roots and shoots of archaeological network analysis: a citation analysis and review of the archaeological use of formal network methods. Archaeol. Rev. Camb. 29 (1), 18–41.

Brughmans, T., Laguna-Palma, D., 2023. Una introducción a la investigación de redes en arqueología: ¿qué es y por qué la necesitamos? Cuadernos de Prehistoria y Arqueología de la Universidad de Granada 33, 11–32. https://doi.org/10.30827/cpag.v33i0.27790.

Brughmans, T., Peeples, M.A., 2023. Network Science in Archaeology. Cambridge University Press.

Castell, W. zu, Schrenk, H., 2020. Computing the adaptive cycle. Sci. Rep. 10 (1), 1–13. https://doi.org/10.1038/s41598-020-74888-y.

Castellano, C., Fortunato, S., Loreto, V., 2009. Statistical physics of social dynamics. Rev. Mod. Phys. 81 (2), 591–646. https://doi.org/10.1103/RevModPhys.81.591.

Chao, A., Chiu, C., 2016. Bridging the variance and diversity decomposition approaches to beta diversity via similarity and differentiation measures. Methods Ecol. Evol. 7 (8), 919–928. https://doi.org/10.1111/2041-210X.12551.

Clarke, D.L., 1962. Matrix analysis and archaeology with particular reference to British beaker pottery. Proc. Prehist. Soc. 28, 371–382. https://doi.org/10.1017/S0079497X00015772.

Clausius, R., 1865a. On different forms of the fundamental equations of the mechanical theory of heat and their convenience for application. Annalen der Physik und Chemie 124, 353–399.

Clausius, R., 1865b. The second law of thermodynamics. The World of Physics 1, 1865.

Collar, A., Coward, F., Brughmans, T., Mills, B.J., 2015. Networks in archaeology: Phenomena, abstraction, representation. J. Archaeol. Method Theor 22 (1), 1–32. https://doi.org/10.1007/s10816-014-9235-6.

Costa, L. da F., Rodrigues, F.A., Travieso, G., Villas Boas, P.R., 2007. Characterization of complex networks: a survey of measurements. Adv. Phys. 56 (1), 167–242. https://doi.org/10.1080/00018730601170527.

Daems, D., 2021. Social Complexity and Complex Systems in Archaeology. Routledge.

Davis, D.S., 2024. Past, present, and future of complex systems theory in archaeology. J. Archaeol. Res. 32 (4), 549–596. https://doi.org/10.1007/s10814-023-09193-z.

De Aguiar, M.A.M., Bar-Yam, I., 2005. Spectral analysis and the dynamic response of complex networks. Phys. Rev. *E* 71 (q), 016106. https://doi.org/10.1103/PhysRevE.71.016106.

Dehmer, M., Mowshowitz, A., 2011. A history of graph entropy measures. Inf. Sci. 181 (1), 57–78. https://doi.org/10.1016/j.ins.2010.08.041.

Dobres, M.-A., Robb, J., 2000. Agency in Archaeology. Psychology Press.

Dunn, O., 1964. Multiple comparisons using rank sums. Technometrics 6, 241–252. *Find this article online, 959*.

Efron, B., Tibshirani, R., 1993. An Introduction to the Bootstrap. Chapman and Hall, New York, NY.

Estrada, E., 2012. The structure of complex networks: theory and applications. American Chemical Society.

Estrada, E., Knight, P.A., 2015. A First Course in Network Theory. Oxford University Press, USA.

Fisher, R.A., 1992. Statistical methods for research workers. In: Kotz, En S., Johnson, N.L. (Eds.), Breakthroughs in Statistics. Springer, New York, pp. 66–70. https://doi.org/10.1007/978-1-4612-4380-9_6.

Folke, C., 2006. Resilience: the emergence of a perspective for social–ecological systems analyses. Glob. Environ. Change 16 (3), 253–267. https://doi.org/10.1016/j.gloenvcha.2006.04.002.

Fortunato, S., 2010. Community detection in graphs. Phys. Rep. 486 (3–5), 75–174. https://doi.org/10.1016/j.physrep.2009.11.002.

Freeman, L., 1977. A set of measures of centrality based on betweenness. Sociometry.

Freeman, L.C., Borgatti, S.P., White, D.R., 1991. Centrality in valued graphs: a measure of betweenness based on network flow. Soc. Netw. 13 (2), 141–154. https://doi.org/10.1016/0378-8733(91)90017-N.

Garmezy, N., 1985. Competence and adaptation in adult schizophrenic patients and children at risk. En *Research in the Schizophrenic Disorders*. Springer, pp. 69–112.

Gheorghiade, P., Vasiliauskaite, V., Diachenko, A., Price, H., Evans, T., Rivers, R., 2023. Entropology: an information-theoretic approach to understanding archaeological data. J. Archaeol. Method Theor 30 (4), 1109–1141. https://doi.org/10.1007/s10816-023-09627-4.

Giddens, A., 1979. Agency, Structure. En *Central Problems in Social Theory*. Springer, pp. 49–95.

Giddens, A., 1984. The Constitution of Society: Outline of the Theory of Structuration. University of California Press.

Gil-Mascarell, M., 1995. Algunas reflexiones sobre el Bronce Valenciano. Saguntum 28, 63–73.

Goh, K.-I., Kahng, B., Kim, D., 2001. Universal behavior of load distribution in scale-free networks. Phys. Rev. Lett. 87 (27), 278701. https://doi.org/10.1103/PhysRevLett.87.278701.

Grimm, S.B., Riel-Salvatore, J., Bradtmöller, M., 2017. Adaptive cycles in archaeology. Quat. Int. 446, 1–2. https://doi.org/10.1016/j.quaint.2017.07.032.

Gronenborn, D., Strien, H.-C., Lemmen, C., 2017. Population dynamics, social resilience strategies, and adaptive cycles in early farming societies of SW Central Europe. Quat. Int. 446, 54–65. https://doi.org/10.1016/j.quaint.2017.01.018.

Gunderson, L.H., 2003. Adaptive dancing: interactions between social resilience and ecological crises. In: En *Navigating social-ecological Systems: Building Resilience for Complexity and Change*. Cambridge University Press, pp. 33–52.
Gunderson, L.H., Holling, C.S., 2002. Panarchy: Understanding Transformations in Human and Natural Systems. Island press.
Hagberg, A., Schult, D., Swart, P., 2005. Networkx: Python Software for the Analysis of Networks. *Mathematical Modeling and Analysis*. Los Alamos National Laboratory.
Harris, C.R., Millman, K.J., Van Der Walt, S.J., Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N.J., others, 2020. Array programming with NumPy. Nature 585 (7825), 357–362.
Hodder, I., 2012. Entangled: an Archaeology of the Relationships Between Humans and Things. Wiley Blackwell.
Hodder, I., Mol, A., 2016. Network analysis and entanglement. J. Archaeol. Method Theor 23, 1066–1094. https://doi.org/10.1007/s10816-015-9259-6.
Hofmann, D., 2019. Commentary: archaeology, archaeogenetics and theory-challenges and convergences. Current Swedish Archaeology 27 (1), 133–140. https://doi.org/10.37718/CSA.2019.07.
Holling, C.S., 1973. Resilience and stability of ecological systems. Annu. Rev. Ecol. Systemat. 4 (1), 1–23. https://doi.org/10.1146/annurev.es.04.110173.000245.
Holling, C.S., 2001. Understanding the complexity of economic, ecological, and social systems. Ecosystems 4 (5), 390–405. https://doi.org/10.1007/s10021-001-0101-5.
Holling, C.S., Gunderson, L., 2002. Resilience and Adaptive Cycles. In: Panarchy: Understanding Transformations in Human and Natural Systems, pp. 25–62.
Hunter, J.D., 2007. Matplotlib: a 2D graphics environment. Comput. Sci. Eng. 9 (3), 90–95.
Irwin-Williams, C., 1977. A network model for the analysis of prehistoric trade. Exchange systems in Prehistory 9 (3), 141–151. https://doi.org/10.1016/B978-0-12-227650-7.50014-6.
Jiménez-Puerto, J., 2022. Conectando con el pasado. Redes sociales en la Prehistoria reciente. Universidad de Valencia (Proquest). https://www.proquest.com/docview/2742640164.
Jiménez-Puerto, J., 2024. Connecting arrowheads: differential transmission of information at the dawn of the Bronze Age. Journal of Lithic Studies 10 (2), 23. https://doi.org/10.2218/jls.7256.
Jiménez-Puerto, J., Bernabeu-Aubán, J., 2023. Linking up Bell beakers in the iberian peninsula. Journal of Archaeological Method and Theory, A Complex Past: Theory and Applications. https://doi.org/10.1007/s10816-023-09625-6.
Johnson, J., Wood, A.M., Gooding, P., Taylor, P.J., Tarrier, N., 2011. Resilience to suicidality: the buffering hypothesis. Clin. Psychol. Rev. 31 (4), 563–591. https://doi.org/10.1016/j.cpr.2010.12.007.
Jost, L., 2006. Entropy and diversity. Oikos 113 (2), 363–375. https://doi.org/10.1111/j.2006.0030-1299.14714.x.
Juan-Cabanilles, J., 2008. El utillaje de piedra tallada en la Prehistoria reciente valenciana: Aspectos tipológicos, estílisticos y evolutivos. Museu de Prehistòria de València.
Kendall, D.G., 1969. Some problems and methods in statistical archaeology. World Archaeol. 1 (1), 68–76. https://doi.org/10.1080/00438243.1969.9979428.
Kendall, D.G., 1971. Abundance matrices and seriation in archaeology. Z. Wahrscheinlichkeitstheor. Verwandte Geb. 17 (2), 104–112. https://doi.org/10.1007/BF00538862.
Kharrazi, A., Yu, Y., Jacob, A., Vora, N., Fath, B.D., 2020. Redundancy, diversity, and modularity in network resilience: applications for international trade and implications for public policy. Current Research in Environmental Sustainability 2, 100006. https://doi.org/10.1016/j.crsust.2020.06.001.
Knappett, C., 2011. An Archaeology of Interaction: Network Perspectives on Material Culture and Society. Oxford University Press.
Kohler, T.A., 2011. Complex Systems and Archaeology. Polity Press.
Kohler, T.A., Crabtree, S.A., Bocinsky, R.K., Hooper, P.L., 2017. Sociopolitical evolution in midrange societies: the Pre-Hispanic Pueblo case. Principles of Complexity: An Introduction to Complex Adaptive Systems and Human Society.
Krioukov, D., Kitsak, M., Sinkovits, R.S., Rideout, D., Meyer, D., Boguñá, M., 2012. Network cosmology. Sci. Rep. 2 (1), 793. https://doi.org/10.1038/srep00793.
Kruskal, W.H., Wallis, W.A., 1952. Use of ranks in one-criterion variance analysis. J. Am. Stat. Assoc. 47 (260), 583–621. https://doi.org/10.1080/01621459.1952.10483441.
Kwiatkowski, D., Phillips, P.C.B., Schmidt, P., Shin, Y., 1992. Testing the null hypothesis of stationarity against the alternative of a unit root. J. Econom. 54 (1–3), 159–178. https://doi.org/10.1016/0304-4076(92)90104-Y.
Latora, V., Marchiori, M., 2001. Efficient behavior of small-world networks. Phys. Rev. Lett. 87 (19), 198701. https://doi.org/10.1103/PhysRevLett.87.198701.
Latour, B., 2007. Reassembling the Social: an Introduction to actor-network-theory. Oxford Univ. Press.
Ligmann-Zielinska, A., Siebers, P.-O., Magliocca, N., Parker, D.C., Grimm, V., Du, J., Cenek, M., Radchuk, V., Arbab, N.N., Li, S., Berger, U., Paudel, R., Robinson, D.T., Jankowski, P., An, L., Ye, X., 2020. 'One size does not fit all': a roadmap of purpose-driven mixed-method pathways for sensitivity analysis of agent-based models. J. Artif. Soc. Soc. Simulat. 23 (1), 6. https://doi.org/10.18564/jasss.4201.
Lin, J., 1991. Divergence measures based on the Shannon entropy. IEEE Trans. Inf. Theor. 37 (1), 145–151. https://doi.org/10.1109/18.61115.
Maier, A., 2015. The central European magdalenian: regional diversity and internal variability. PaleoAnthropology 65–66. https://doi.org/10.1007/978-94-017-7206-8, 2015.
Mann, H.B., Whitney, D.R., 1947. On a test of whether one of two random variables is stochastically larger than the other. Ann. Math. Stat. 50–60.
Massey, F.J., 1951. The kolmogorov-smirnov test for goodness of fit. J. Am. Stat. Assoc. 46 (253), 68–78. https://doi.org/10.1080/01621459.1951.10500769.
McKinney, W., 2010. Data structures for statistical computing in python. Proceedings of the Python in Science Conference 445, 56.
Mills, B.J., Clark, J.J., Peeples, M.A., Haas, W.R., Roberts, J.M., Hill, J.B., Huntley, D.L., Borck, L., Breiger, R.L., Clauset, A., Shackley, M.S., 2013. Transformation of social networks in the late pre-hispanic US southwest. Proc. Natl. Acad. Sci. 110 (15), 5785–5790. https://doi.org/10.1073/pnas.1219966110.
Mowshowitz, A., Dehmer, M., 2012. Entropy and the complexity of graphs revisited. Entropy 14 (3), 559–570. https://doi.org/10.3390/e14030559.
Newman, M.E.J., 2003. The structure and function of complex networks. SIAM Rev. 45 (2), 167–256. https://doi.org/10.1137/S003614450342480.
Newman, M., 2012. Networks: an Introduction. Oxford university press.
Newman, M., 2018. Networks. Oxford university press.
Newman, M.E.J., Girvan, M., 2004. Finding and evaluating community structure in networks. Physical Review E 69 (2), 026113. https://doi.org/10.1103/PhysRevE.69.026113.
Pardo-Gordó, S., Bernabeu Aubán, J., Jiménez-Puerto, J., Armero, C., García-Donato, G., 2022. The chronology of archaeological assemblages based on an automatic Bayesian procedure: Eastern Iberia as study case. J. Archaeol. Sci. 139, 105555. https://doi.org/10.1016/j.jas.2022.105555.
Pedregosa, F., 2011. Scikit-learn: machine learning in python Fabian. J. Mach. Learn. Res. 12, 2825.
Peeples, M.A., 2019. Finding a place for networks in archaeology. J. Archaeol. Res. 27 (4), 451–499. https://doi.org/10.1007/s10814-019-09127-8.
Perreault, C., 2019. The Quality of the Archaeological Record. University of Chicago Press. https://doi.org/10.7208/9780226631011.
Perrings, C., 2006. Resilience and sustainable development. Environ. Dev. Econ. 11 (4), 417–427. https://doi.org/10.1017/S1355770X06003020.
Plotly Technologies Inc, 2015. Collaborative Data Science, 376. Plotly Technologies Inc Montral, Montreal.
Prigogine, I., Stengers, I., 2018. Order out of Chaos: Man's New Dialogue with Nature. Radical Thinkers. Verso.
Reynoso, C., 2011. *Redes sociales y complejidad: modelos interdisciplinarios en la gestión sostenible de la sociedad y la cultura*. Sb Buenos Aires. http://www.academia.edu/download/32184999/Redes-y-complejidad2.pdf.
Rivers, R., 2016. Can archaeological models always fulfill our prejudices. In: En *the Connected Past: Challenges to Network Studies in Archaeology and History*, pp. 123–147. https://doi.org/10.1093/oso/9780198748519.003.0014.
Rosen, A.M., Rivera-Collazo, I., 2012. Climate change, adaptive cycles, and the persistence of foraging economies during the late Pleistocene/Holocene transition in the Levant. Proc. Natl. Acad. Sci. 109 (10), 3640–3645. https://doi.org/10.1073/pnas.1113931109.
Said, S.E., Dickey, D.A., 1984. Testing for unit roots in autoregressive-moving average models of unknown order. Biometrika 71 (3), 599–607. https://doi.org/10.1093/biomet/71.3.599.
Schaub, M.T., Delvenne, J.-C., Rosvall, M., Lambiotte, R., 2017. The many facets of community detection in complex networks. Applied Network Science 2 (1), 4. https://doi.org/10.1007/s41109-017-0023-6.
Schwengber, L.R., Prado, S.D., Dahmen, S.R., 2021. *An entropy-based, scale-dependent centrality* (Versión 1). arXiv. https://doi.org/10.48550/ARXIV.2108.09248.
Shannon, C.E., 1948. A mathematical theory of communication. Bell System Technical Journal 27 (3), 379–423. https://doi.org/10.1002/j.1538-7305.1948.tb01338.x.
Shapiro, S.S., Wilk, M.B., 1965. An analysis of variance test for normality (complete samples). Biometrika 52 (3/4), 591. https://doi.org/10.2307/2333709.
Shennan, S., Downey, S.S., Timpson, A., Edinborough, K., Colledge, S., Kerig, T., Manning, K., Thomas, M.G., 2013. Regional population collapse followed initial agriculture booms in mid-Holocene Europe. Nat. Commun. 4. https://doi.org/10.1038/ncomms3486.
Shetty, J., Adibi, J., 2005. Discovering important nodes through graph entropy the case of enron email database. In: Proceedings of the 3rd International Workshop on Link Discovery, pp. 74–81.
Spearman, C., 1961. The proof and measurement of association between two things. In: Jenkins, En J.J., Paterson, D.G. (Eds.), Studies in Individual Differences: the Search for Intelligence. Appleton-Century-Crofts, pp. 45–58. https://doi.org/10.1037/11491-005.
Surovell, T.A., Byrd Finley, J., Smith, G.M., Brantingham, P.J., Kelly, R., 2009. Correcting temporal frequency distributions for taphonomic bias. J. Archaeol. Sci. 36 (8), 1715–1724. https://doi.org/10.1016/j.jas.2009.03.029.
Tarradell, M., 1965. El problema de las diversas áreas culturales de la Península Ibérica en la Edad del Bronce. Miscelánea en Homenaje al abate H. Breuil (1877-1961). Barcelona: diput. Prov.-Inst. Prehistoria y Arqueología. Barcelona 2, 423–430.
Thiele, J.C., Kurth, W., Grimm, V., 2014. Facilitating parameter estimation and sensitivity analysis of agent-based models: a cookbook using NetLogo and «R. J. Artif. Soc. Soc. Simulat. 17 (3), 11. https://doi.org/10.18564/jasss.2503.
Tukey, J.W., 1949. Comparing individual means in the analysis of variance. Biometrics 5 (2), 99. https://doi.org/10.2307/3001913.
Turchin, P., 2003. Evolution in population dynamics. Nature 424 (6946), 257–258.
Tutzauer, F., 2007. Entropy as a measure of centrality in networks characterized by path-transfer flow. Soc. Netw. 29 (2), 249–265. https://doi.org/10.1016/j.socnet.2006.10.001.
Ulanowicz, R.E., Goerner, S.J., Lietaer, B., Gomez, R., 2009. Quantifying sustainability: resilience, efficiency and the return of information theory. Ecol. Complex. 6 (1), 27–36. https://doi.org/10.1016/j.ecocom.2008.10.005.
Van Oyen, A., 2015. Actor-network Theory's take on archaeological types: becoming, material agency and historical explanation. Camb. Archaeol. J. 25 (1), 63–78. https://doi.org/10.1017/S0959774314000705.

Virtanen, P., Gommers, R., Oliphant, T.E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., Van Der Walt, S.J., Brett, M., Wilson, J., Millman, K.J., Mayorov, N., Nelson, A.R.J., Jones, E., Kern, R., Larson, E., et al., 2020. SciPy 1.0: fundamental algorithms for scientific computing in python. Nat. Methods 17 (3), 261–272. https://doi.org/10.1038/s41592-019-0686-2.

Walker, B., Salt, D., 2012. Resilience Thinking: Sustaining Ecosystems and People in a Changing World. Island press.

Walker, B., Carpenter, S., Anderies, J., Abel, N., Cumming, G., Janssen, M., Lebel, L., Norberg, J., Peterson, G.D., Pritchard, R., 2002. Resilience management in social-ecological systems: a working hypothesis for a participatory approach. Conserv. Ecol. 6 (1).

Walker, B.H., Anderies, J.M., Kinzig, A.P., Ryan, P., 2006. Exploring resilience in social-ecological systems through comparative studies and theory development: introduction to the special issue. Ecol. Soc. 11 (1).

Wang, B., Tang, H., Guo, C., Xiu, Z., 2006. Entropy optimization of scale-free networks' robustness to random failures. Phys. Stat. Mech. Appl. 363 (2), 591–596. https://doi.org/10.1016/j.physa.2005.08.025.

Wasserman, S., Faust, K., 1994a. Social Network Analysis: Methods and Applications. Cambridge University Press.

Wasserman, S., Faust, K., 1994b. Social Network Analysis: Methods and Applications. Cambridge University Press.

Weiberg, E., 2012. What can Resilience Theory Do for (Aegean) Archaeology? En *Matters of Scale*. Stockholm University.

Weinelt, M., Kneisel, J., Schirrmacher, J., Hinz, M., Ribeiro, A., 2021. Potential responses and resilience of Late Chalcolithic and early Bronze Age societies to mid-to Late Holocene climate change on the southern Iberian Peninsula. Environ. Res. Lett. 16 (5), 055007.

Wihler, T.P., Bessire, B., Stefanov, A., 2012. Computing the entropy of a large matrix. https://doi.org/10.48550/ARXIV.1209.2575.

Wu, L., Tan, Q., Zhang, Y., 2013. Network connectivity entropy and its application on network connectivity reliability. Phys. Stat. Mech. Appl. 392 (21), 5536–5541. https://doi.org/10.1016/j.physa.2013.07.007.

Zhao, Y., Levina, E., Zhu, J., 2011. Community extraction for social networks. Proc. Natl. Acad. Sci. 108 (18), 7321–7326. https://doi.org/10.1073/pnas.1006642108.

Zimmerman, D.W., 2004. A note on preliminary tests of equality of variances. Br. J. Math. Stat. Psychol. 57 (1), 173–181. https://doi.org/10.1348/000711004849222.