

Title

Similarity Network Fusion: Understanding Patterns and their Spatial Significance in Archaeological Datasets

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Abstract

Since its earliest application in the 1970s, network analysis has become increasingly popular in both theoretical and GIS-based archaeology. Yet, applications of material networks remained relatively restricted. This paper describes a specific kind of material network, so called similarity networks, and presents a new network analysis method to approach them: Similarity Network Fusion (SNF).

Most archaeological applications of material networks approach similarity by simply quantifying the number of co-occurrences of certain traits between two nodes, without considering the relative importance of these traits for the whole network. Statistical similarity measures have so far only been applied to a handful of case studies. The similarity network analysis outlined in this paper relies on SNF, a method common in genomic studies. SNF is based on the iterative integration of similarity networks derived from multiple datatypes for the same set of samples, allowing the application of a wide range of similarity indices. It has proven to be particularly robust to heterogenous and noisy datasets containing a small number of samples, but a large number of measurements, scale differences, and collection biases.

In a case study, I applied SNF to Early Bronze Age, Middle Bronze Age, and Late Iron Age burial sites in Dorset, resorting to data published by the *Grave Goods Project*. To enhance the understanding of the resulting networks and topological clusters, the network was spatially represented and the clusters were correlated with five further attributes; physiographic areas, the sex of the buried individuals, the ratio of objects per grave, whether isotopic analyses suggest that the buried people were local inhabitants or moved into the area of their burial, or whether there is an association between clusters and a finer chronological subdivision of sites. The network analysis and the topological clustering of the sites revealed at least two possible spatial clusters and two statistically significant correlations between clusters and further attributes of the burial sites. These results clearly suggest the great potential of SNF for analysing archaeological datasets, unveiling patterns within the archaeological record, and understanding the significance of these patterns for the structuration of the past landscape.

Introduction

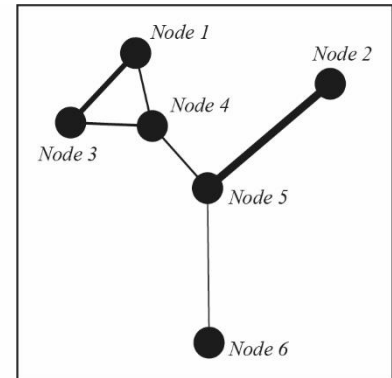
Network analysis¹ has proven to be a powerful analytical tool to study and visualise the significance of relationships between past and present social, cultural, and material entities (Collar et al., 2015). For archaeological applications, it has been argued that one of the major advantages of network analysis is its great flexibility and versatility in use. Depending on the research question, virtually every entity can be studied meaningfully through a network approach, regardless of its size or materiality. Similarly, edges can represent a multitude of different relationships such as social connections, economic interactions, flows of ideas and goods, geographical proximity, or material similarity (Brughmans et al., 2016). Furthermore, due to the spatial reference of archaeological data, networks in archaeology can be analysed and visualised both in relational space, for example through adjacencies matrices or node-link-diagrams (cf. fig. 1), or in absolute space within a geographical information system (Knappet, 2013; Brughmans & Peeples, 2020).

¹ A network is a representation of the structure of relationships or connections—often called edges—between certain kinds of elements—often called nodes—of interest (Brughmans & Peeples, 2020, p. 273). For further reading: Brughmans et al., 2023.

Archaeological networks, therefore, have the potential of bridging simultaneously a diverse range of social and geographical scales of analysis and overcoming the problematic split between geometric and relational perspectives (Knappet, 2011; Knappet, 2013; Knappet, 2016). Network analysis, moreover, provides archaeology with a multitude of well-established exploratory network techniques and statistical network measures, representing powerful tools to detect patterns and clusters in networks as well as to describe local and global measures, revealing structural properties of single nodes or of the network as a whole (Brughmans & Peeples, 2020).

	Node 1	Node 2	Node 3	Node 4	Node 5	Node 6
Node 1			2	0.75		
Node 2					3	
Node 3	2			1		
Node 4	0.75		1		0.75	
Node 5		3		0.75		0.5
Node 6					0.5	

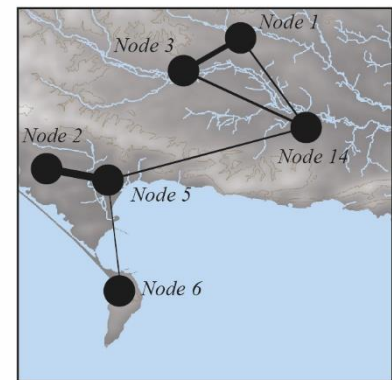
Adjacency Matrix



Node-Link-Diagram

Edge ID	Source Node	Target Node	Edge strength
1	1	3	2
2	1	4	0.75
3	3	4	1
4	5	2	3
5	5	4	0.75
6	5	6	0.5

Edge List



Spatial Network

Figure 1 - Different types of network representations of the same Network. After Brughmans & Peeples, 2020, Figure 15.1. Background © Environment Agency.

Since its earliest application in the 1970s and particularly in the last decade, network analysis became increasingly popular in both theoretical and GIS-based archaeology (Prignano et al., 2017; Brughmans & Peeples, 2020; Donnellan, 2020). However, applications of material networks remained astonishingly restricted. Material networks are a specific kind of archaeological network whose edges are defined by aspatial contextual information such as geochemically sourced materials, shared presence of certain objects, or similarities in material assemblages (Brughmans & Peeples, 2020, p. 277). By relating these networks to the geographical space, material networks appear particularly suitable to study the structuration of past landscapes and understanding the spatial significance of past social and cultural processes.

In this paper I will further explore the potential of material network analysis. The focus of the paper is on a specific kind of material network, so called similarity networks. I will investigate similarity networks through a case study, conducted with data from the numerous Prehistoric burials in Dorset (UK), and a new network analysis technique developed for genomic studies: Similarity Network Fusion (SNF).

Similarity Networks

In general, similarity networks are a set of material network analysis methods, which use measures of similarity—for instance between assemblages of material culture—to define edges among archaeological sites (Brughmans & Peeples, 2020, p. 277). Originally, similarity networks are simple bipartite networks, consisting solely of two classes of nodes; the archaeological context (i. e., a site), and attributes associated with this context (i. e., artefact types). However, unlike normal binary affiliation networks, the strength of the edges between nodes is weighed by the frequency of their shared attributes (Prignano et al., 2017). Within similarity network analysis, the strength of similarity between archaeological assemblages is often interpreted as proxy of exchange, interaction, population movement, transmission of knowledge, or cultural relatedness (Peeples et al., 2016; Prignano et al., 2017).

Most archaeological applications of material culture networks rather seem to approach similarity by simply quantifying the number of co-occurrences of certain traits between two nodes, without considering the relative importance of these traits for the whole network (i.a. Sindbaek, 2007; Mizoguchi, 2009; Blake, 2013; Östborn & Gerding, 2015; Feugnet et al., 2017). In order to approach the relative importance of a network connection, statistical similarity measures need to be applied. There are many different similarity measures which all have slightly different contextual meaning and have different suitabilities for certain archaeological questions (cf. Habiba et al., 2018). Yet, so far only a handful of archaeological case studies have used such similarity coefficients. Probably the first application of a similarity coefficient in archaeology was undertaken by Morgan and Whitelaw (1991), using dissimilarity indices to relate different Geometric pottery assemblages in the Greek Argive region. More than 20 years later, Golitko et al. (2012) used the Brainerd-Robinson coefficient to analyse similarities among the composition of obsidian sources of Mayan stone tool assemblages, while Mills et al. (2013) applied the same approach to pre-Hispanic ceramic and obsidian assemblages from the south-western United States. De Groot (2019) resorted to Jaccard and Kulczynski-2 measures in order to assess similarity between Neolithic pottery assemblages in Eastern Anatolia, the Aegean, and the Balkans. Bourgeois and Kroon (2017), lastly, used the cosine similarity index for the estimation of the similarity between Northern European Corded Ware graves. For the cosine similarity index each observation consisting of different variable attributes is converted to a vector in virtual space; the similarity between two observations is expressed as differences between the angles of their vectors (Bourgeois & Kroon, 2017).

The similarity network analysis outlined in the case study below relies on so called Similarity Network Fusion (SNF), a method commonly applied in genomic studies (Wang et al., 2014). SNF is based on the integration of similarity networks derived from multiple datatypes (i. e., different object types) for the same set of samples (i. e., sites). In a first step, SNF calculates a similarity network between each pair of samples for each of the datatypes, allowing the application of a wide range of similarity indices. Secondly, all of these networks are fused into a single similarity network, by using a nonlinear, iterative approach; based on message-passing theory, every network is updated and made more similar to the other networks after each iteration, before finally converging to a single network. In the iterative process, strong similarities tend to be emphasised, while weak similarities are down-weight through a K-nearest neighbours procedure, reducing the noise in the final network and only retaining weak relationships, being consistent across the whole dataset. SNF has proven to be particularly robust to heterogenous and noisy datasets, containing only a small number of samples, but a large amount of measurements, scale differences, and collection biases. Arguably, these data conditions are not only common for genomic datasets, but are also typical for archaeological data. Furthermore, apart from integrating data, SNF provides a set of additional network techniques (i.e. spectral clustering), which are especially suitable for detecting subtypes and clusters in topological networks.

Case Study

Material and Methods

To further expand on the functionality, performance, and potential of similarity networks and SNF for archaeological purposes, I conducted a similarity analysis of Late Prehistoric burial sites in Dorset. Subsequently, I understand burials as materialisation of past social, ritual, and cultural actions, both

representing and constituting social and cultural meaning (cf. Ekengren 2013). By representing material networks between roughly contemporary burial sites, the objective of the analysis is to get insights into the social, cultural, and ritual structuration of the landscape. Central to a landscape perspective is a more holistic view of human actions, taking into consideration the relationship between sites as well as humanly and non-humanly created features. As such, landscape is understood as cause and outcome of human actions, crossing the distinction between nature and culture (cf. Gosden et al., 2021, 18).

The data used for conducting the SNF analysis were derived from the published database of the *Grave Goods project* (Cooper et al., 2022). Within six regional study areas, the Grave Goods project analysed diachronically and at a series of scales material culture and mortuary contexts during the Neolithic to the Iron Age period. The six regions were chosen, taking into account strong histories of investigation, the accessibility of records, and grave goods traditions (Cooper et al., 2020, p. 2). The database is based on information from the Historic Environment Record and was further enhanced by published and unpublished data (Cooper et al., 2020). Though the burial data were subject to extensive analyses, which were only recently published (Cooper et al., 2022), neither addressed the project explicitly a network approach to the collected data, nor appears the abundant contextual burial information, yielded by the project, to be exploited to its full potential.

I choose Dorset as area of investigation for the SNF analysis, as it is the region with the most extensive site record analysed by the Grave Goods project. To roughly fulfil the presupposition of contemporaneity, I only used similarity measures for sites dating to the same subperiod. Additionally, I solely took sites dating to the Early Bronze Age (EBA, 2200–1500 BCE, 115 burials), Middle Bronze Age (MBA, 1500–1150 BCE, 46 burials), and Late Iron Age (LIA, 100 BCE–40 AD, 23 burials) into consideration, as from remaining subperiods the burials did not appear numerous enough for meaningful network analyses. Since the Grave Goods project stored the spatial data on the level of the site, I defined inter-site relations as scale of analysis.

In order to explore similarity-relationships, I prepared two sets of different datatypes for the sites of each subperiod. The first set attempted to give a more holistic impression of burial rituals covering a great variety of aspects of the burial data. Namely, the datatypes encompassed grave hierarchy, grave type, human remains, the associated monument types, numbers of buried individuals, the unspecific grave good type, the placement of the objects in relation to the body, and the materials of the grave goods (cf. tab. 1).

Dataset 1	
Categories:	Examples:
Grave Hierarchy	Primary, secondary
Grave Type	Cist, mound, etc.
Human Remains	Inhumation, cremation
Monument Type	Burial, barrow, etc.
Placement of the Object	Torso, head, etc.
Grave Good Type	Ceramics, Dagger, etc.
Materials	Bronze, gold, etc.
Number of Buried Individuals	1, 2, 3...

Table 1 – Dataset 1, showing all categories of the burial data included in the holistic SNF analysis and examples for the kind of information recorded by the grave goods project for each datatype.

Since archaeology traditionally assigns to the type of object high cultural and chronological significance (Ekengren, 2013), the second set of datatypes focused on the grave goods themselves. This set solely included the specific grave good type and the placement of the objects in relation to the buried body (cf. tab. 2).

Dataset 2	
Categories:	Examples:
Grave Good Type	Ceramics, dagger, etc.
Placement of the Object	Torso, head, etc.

Table 2 – Dataset 2, showing all categories of the burial data included in the object-related SNF analysis and examples for the kind of information recorded by the grave goods project for each datatype.

Since SNF analyses need contingency tables as input, each datatype first needed to be reformatted accordingly; this pre-processing was conducted in Excel and SPSS and resulted in tables, containing information about the absence or presence of all attributes of a datatype for each site. I conducted SNF analysis in Python, using the SNFpy package (cf. Markello, 2018; rmarkello / snfpy, 2022). A recent study (Prignano et al., 2017) reached the conclusion that Network measures such as Weighted Degree Centrality and Betweenness Centrality indexes of the Brainerd-Robinson coefficient—the most common coefficient in archaeological applications of similarity network analysis—highly depend on the number of samples. For incomplete datasets, the Brainerd-Robinson coefficient therefore does not seem to be the best performing similarity index to study the strongest network connections. Instead, I applied the well-established cosine coefficient for the creation of the similarity networks for the different datatypes (cf. Bourgeois & Kroon, 2017), which is particularly effective for datasets with many different attributes and to consider non-uniform significance (Habiba et al., 2018). The python SNF algorithm displays the fused network as adjacency matrix, showing the similarity between each pair of sites. After all networks had been fused with each other, I determined the optimal number of clusters in the network using the `get_n_clusters` function and grouped the sites accordingly. The `get_n_clusters` function is based on a spectral clustering approach (rmarkello / snfpy, 2022). In spectral clustering, the eigenvalues or spectrum of the similarity matrix are used to reduce dimensions and translate the similarities in a Laplacian graph. K-means clustering is then applied to the eigenvectors of the Laplacian graph to establish the optimal number of clusters.

Together with the fused similarity matrix, I subsequently exported the resulting clusters of sites. The fused similarity network was reformatted as edge list and imported into ArcGIS pro. Since the results of the SNF analysis roughly vary between values of 0 and 0.6, in ArcGIS Pro I used the Standardize Field tool (Esri, 2022a) to exclude outliers of very high similarity values, occurring due to the great similarity which samples have with themselves, and to rescale the remaining values between 0 and 1. Between all sites of each period, I created a non-planar Origin-Destination Cost Matrix (Esri, 2022b), defining each site as a node connected by edges to every other site. The edges of the network were then joined with the results of the SNF analysis. To get an assessable impression of possible relationships in the area of research, I restricted the representation of the edges to the 25 highest similarities and weighed them according to their network importance. The cluster classification of the sites was joined with the nodes of the networks, enabling a representation of the topological clusters in geographical space.

Discussion

Dorset is a county in southern England, bordering the English channel to the south. Apart from a long stretching coastline, Dorset is characterised by a varied hinterland with chalk downs, limestone ridges, and low-lying clay valleys. In the earliest part of the EBA, burials were mainly constructed as single inhumation graves with a large number of deposits under mounds of a diverse range of sizes and forms (Cullingford 1980). Not uncommonly, these mounds were designed as multiphase monuments. In the later EBA, cremations under single-phase mounds predominated (Bradley 2019, 173; Garwood 2007). In the MBA, cremation burials likewise prevailed. Some were still placed under barrows, while occasionally, they also occurred in cemeteries. MBA burials were usually associated with ceramic vessels and less commonly with metalwork and other objects (Cooper et al. 2022). In the LIA, inhumation graves were usually organised in cemeteries. They were associated with a variety of objects such as objects of personal adornment, tools, or ceramics.

With the exception of the clusters reconstructed from EBA burials (i. e. fig. 3 and 6), most clusters derived from the first and second dataset appear quite different from each other (i. e. figs. 4 and 7, and figs. 5 and 8). In general, the topological clusters reveal hardly any clear patterns in geographical space. Some notable exceptions are conspicuous clusters of LIA burials in southern Dorset, visible on both the extensive and the object focused network analysis (cf. black cluster fig. 5, white cluster fig. 8) as well as clusters of MBA sites derived from the network analysis with the first set of datatypes (fig. 4); taking the spatial distribution of the white and the black clusters into account, it almost appears as if these groups separate into a northern and a southern pattern. However, the third, most comprehensive red cluster seems to distort this clear picture. Furthermore, in both datasets and across almost all periods some clusters seem to be more closely connected than others. Most obvious this can be seen in the network of MBA sites derived from dataset 1 (cf. fig. 4). Here, the strongest network connections are almost exclusively between points of the white cluster.

To enhance the understanding of the meaning and relevance of the topological clusters and strongest network edges, I evaluated the spatial correlations of the clusters with five further attributes. Namely, these five attributes were the association of the burials with specific physiographic areas, the sex of the buried individuals of a site, the ratio of objects per grave, whether isotopic analyses suggest that the buried people were local inhabitants or moved into the area of their burial, or whether there is an association between clusters and a finer chronological subdivision of sites.

Landscape

The association of burial clusters with a certain landscape was approached by using the National Character Area Profiles (Natural England, 2022). National Character Areas are a classification of England by regions, which have a recognisable character and are bounded by natural lines in the landscape. Though the character of landscapes arguably has significantly changed since the Late Prehistory and strongly relies on our modern way of perceiving these areas, since National Character Areas are based on the natural structuration and appearance of the landscape, they seem a more accurate approximation of possible past landscape divisions than modern political borders.



Figure 2 - National Character Areas of Dorset. Background © Environment Agency. Natural character areas © Natural England.

In total, the area of Dorset consists of nine National Character Areas (cf. fig. 2). Yet, depicting the different networks against the background of the National Character Areas does not suggest a correlation between the topological clusters and these nine regions. In fact, apart from the geographically very restricted clusters visible in the LIA object network (cf. white cluster fig. 8), there seems to be not a single cluster which exclusively is located in only one National Character Area.

Sex Affiliation

The association of a site with a specific sex was reconstructed on the basis of data of anthropological sex determinations of human remains available within the Grave Goods project database. Since some sites encompassed several human remains with different sexes, for the purpose of this analysis the sites were

reclassified in the attributes Male, Female, Subadult, and——if more than one sex was determined at the same site——Mixed according to their predominant association with a certain sex.

Similar as with the landscape classification, there does not seem to be an obvious correlation between the burial clusters and the different sex categories; while within the EBA and LIA networks there is no cluster consisting solely or predominantly of one sex class (cf. fig. 5 and 8), the white cluster in the MBA network derived from a diverse set of datatypes only comprises female burials (fig. 4). However, since most sex affiliations of the cluster's sites are unknown and the potential relationship between the cluster and burials does not seem to be mutually exclusive, it appears rather doubtful that there is a correlation between the cluster and the sex classes at all.

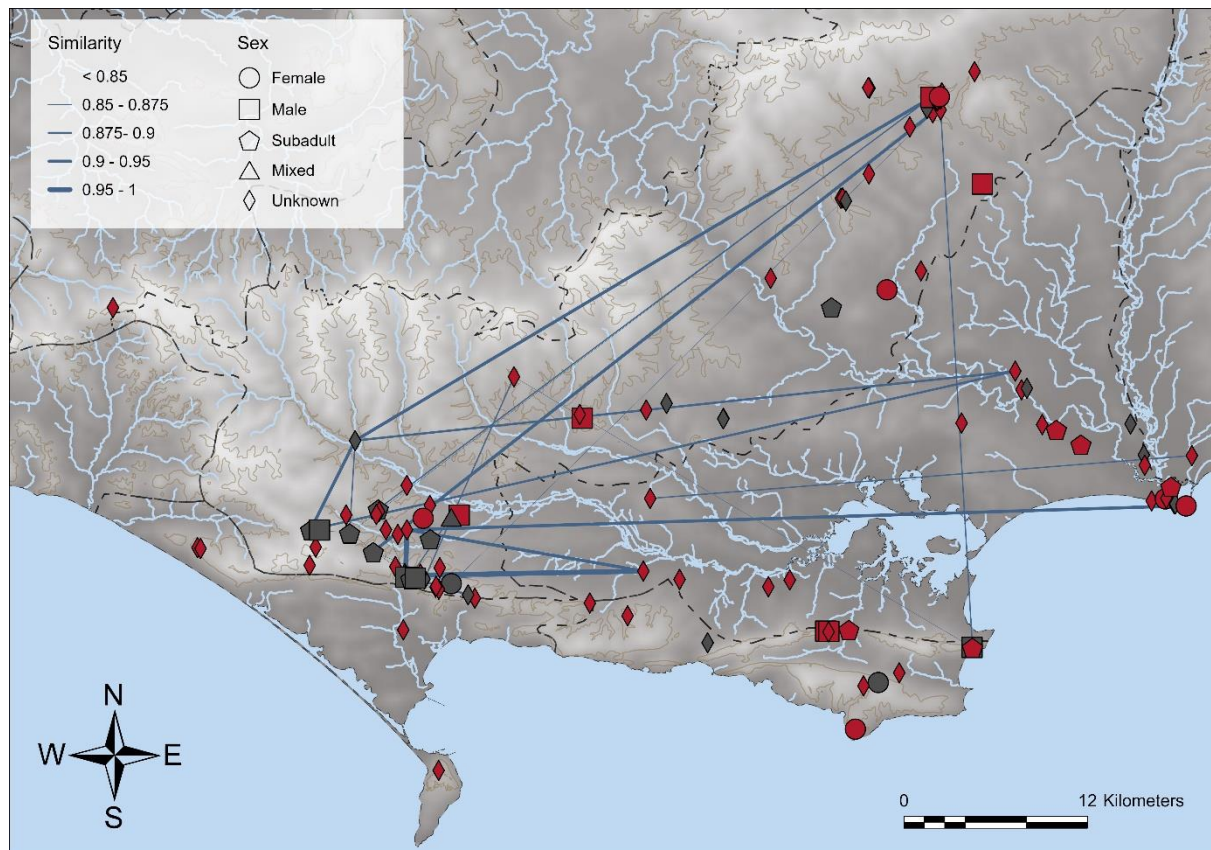


Figure 3 - Similarity network derived from the first datatypes of Early Bronze Age sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red), and sex classification of sites. Background © Environment Agency. Natural character areas © Natural England.

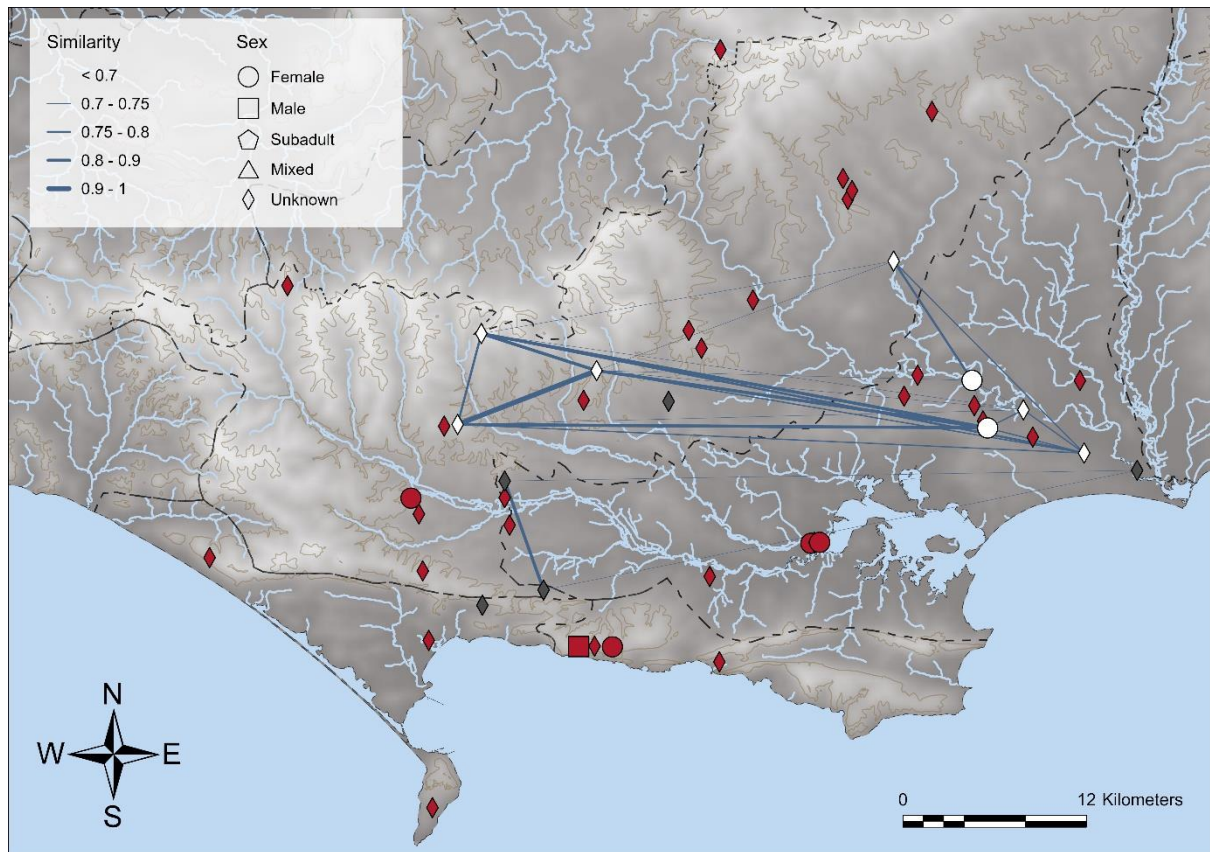


Figure 4 - Similarity network derived from the first datatypes of Middle Bronze Age sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red, white), and sex classification of sites. Background © Environment Agency. Natural character areas © Natural England.

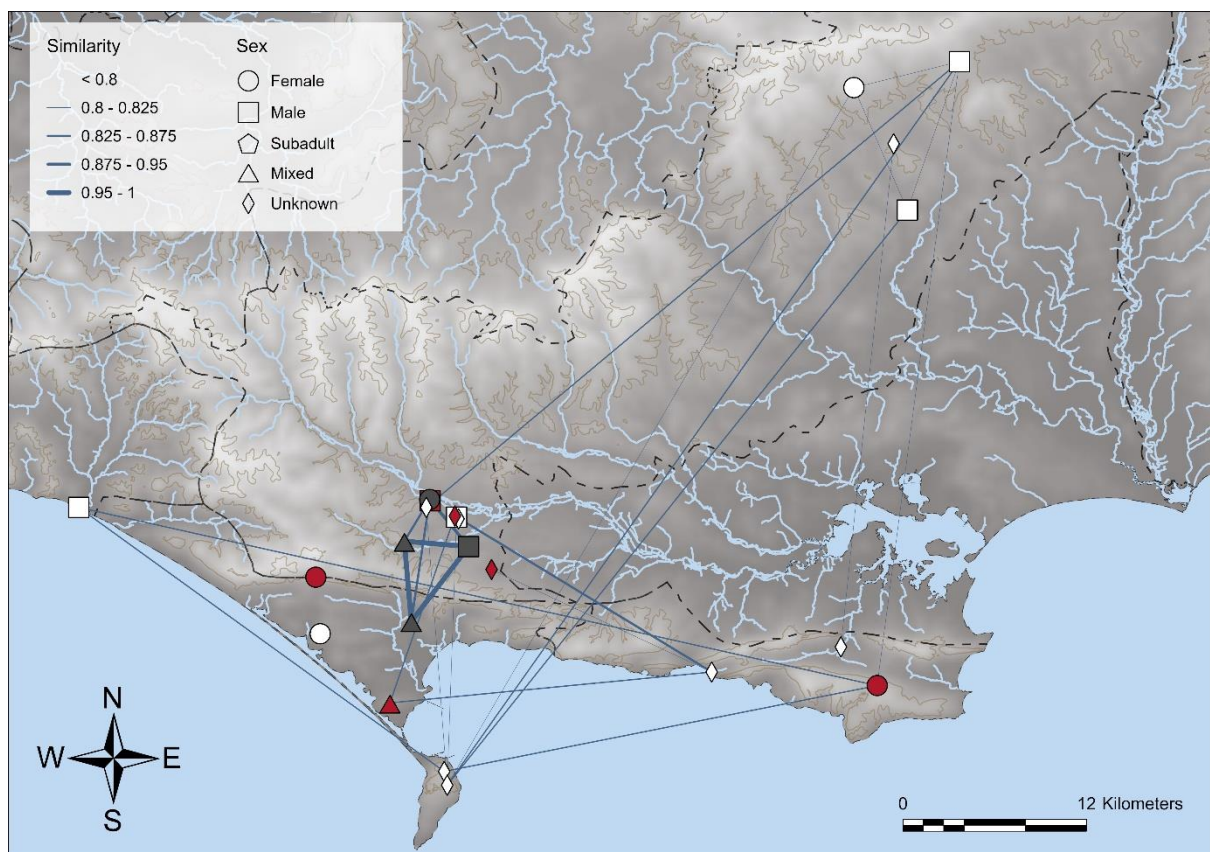


Figure 5 - Similarity network derived from the first datatypes of Late Iron Age sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red, white), and sex classification of sites. Background © Environment Agency. Natural character areas © Natural England.

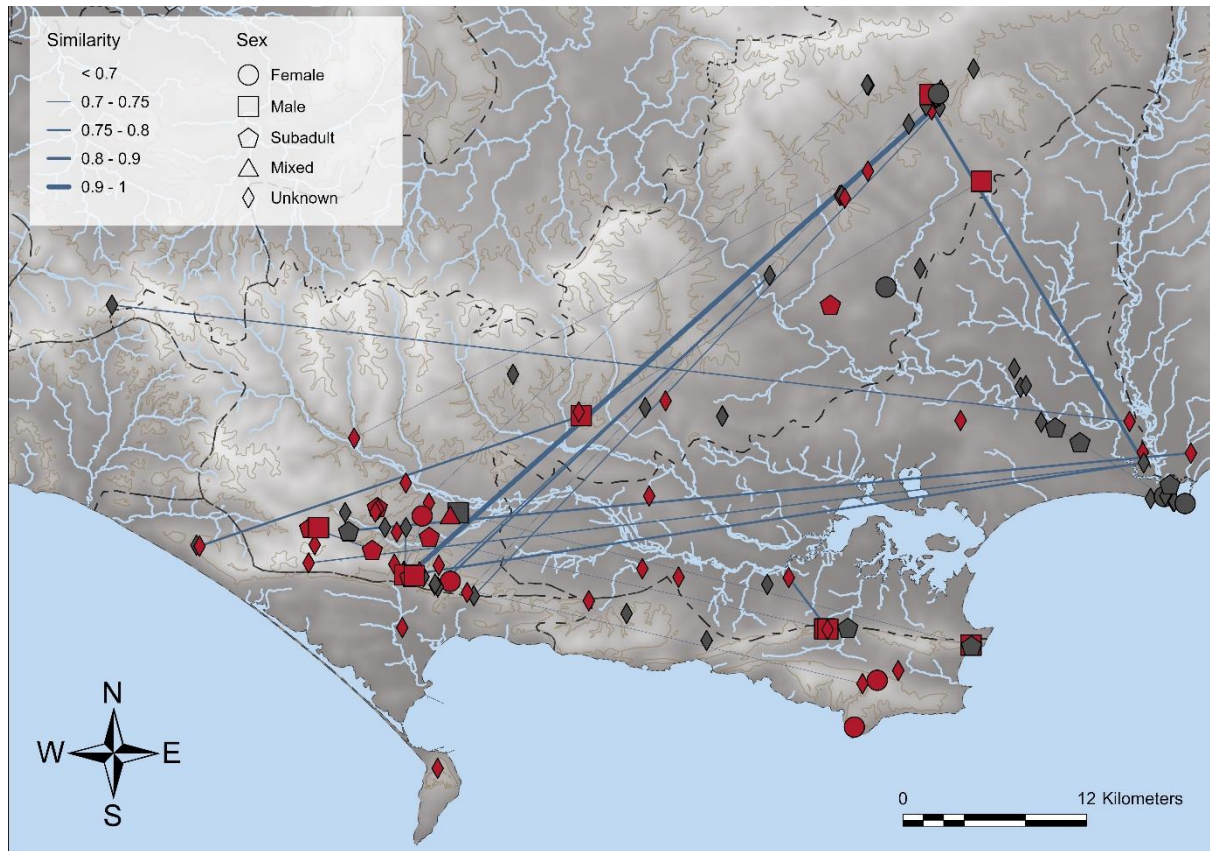


Figure 6 - Similarity network derived from the second datatypes of Early Bronze Age sites in Dorset, depicting 25 strongest network connections, topological clusters (black, red), and sex classification of sites. Background © Environment Agency. Natural character areas © Natural England.

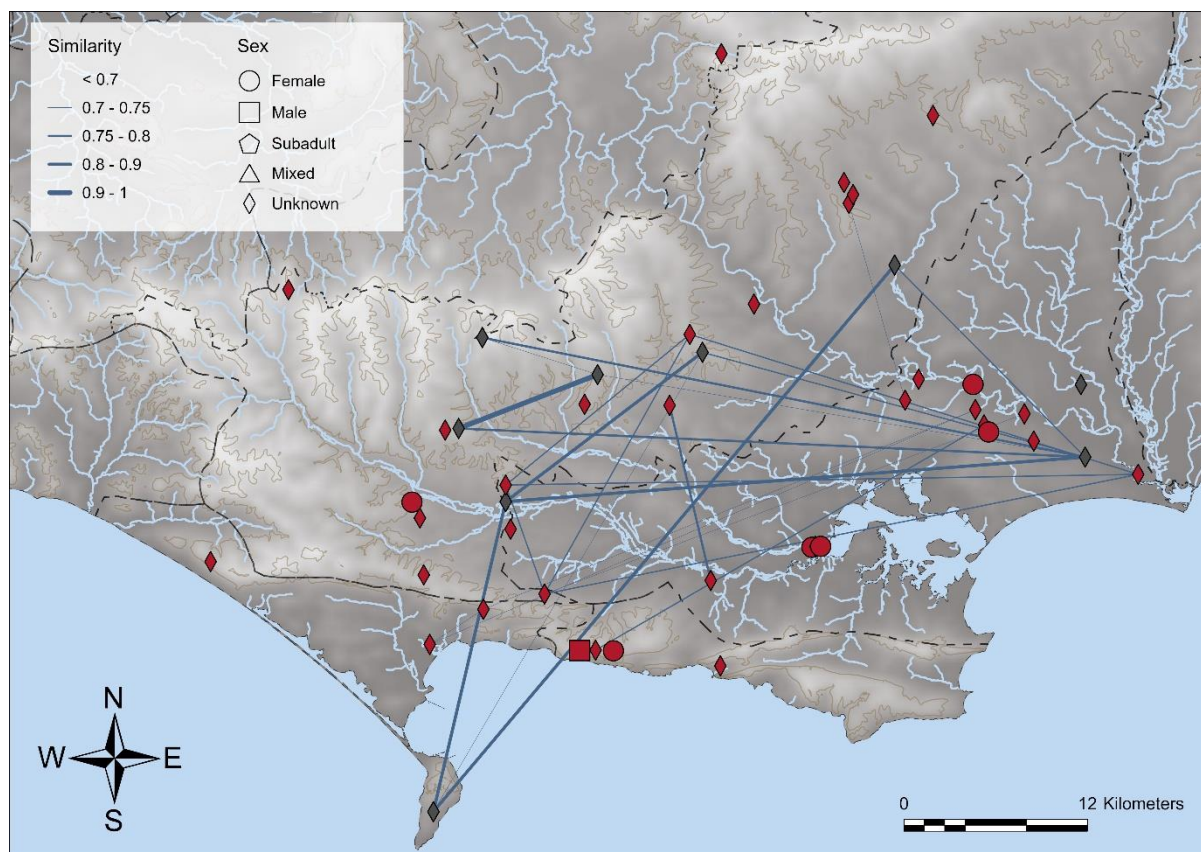


Figure 7 - Similarity network derived from the second datatypes of Middle Bronze Age sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red), and sex classification of sites. Background © Environment Agency. Natural character areas © Natural England.

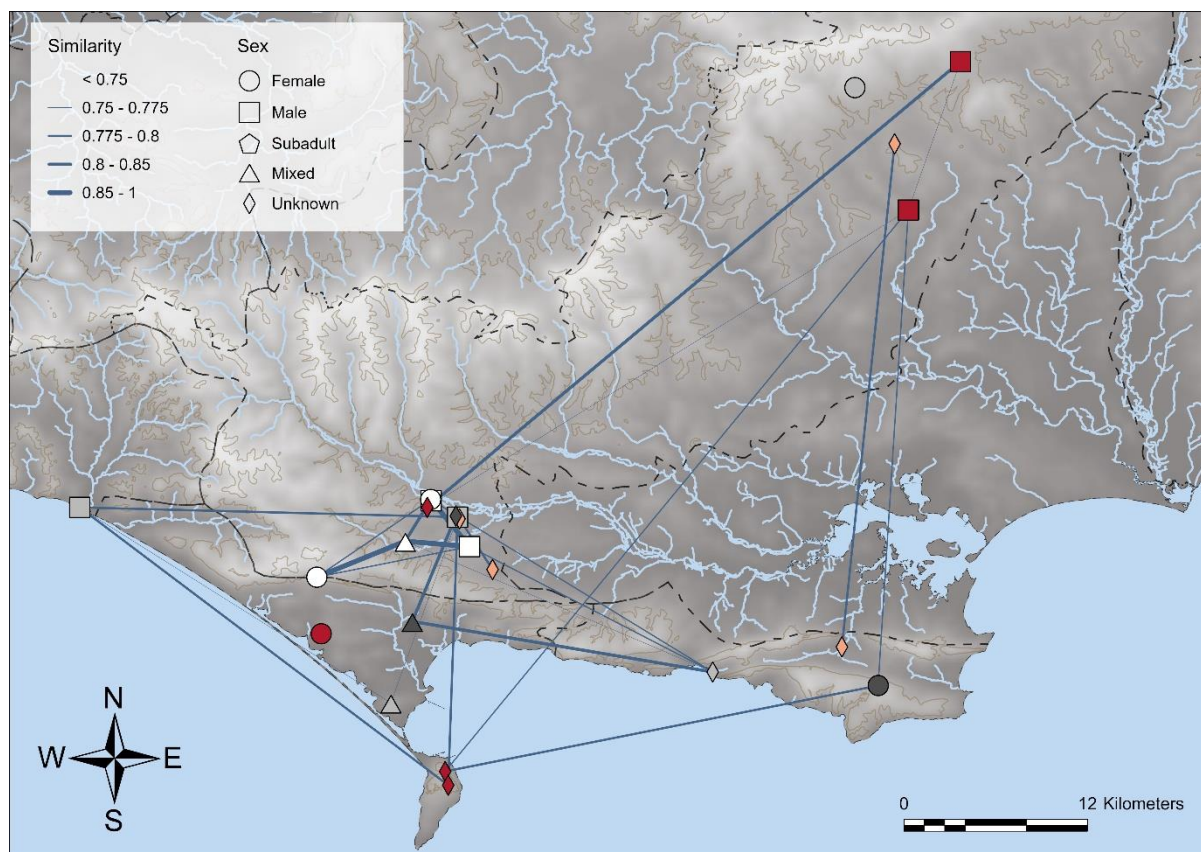


Figure 8 - Similarity network derived from the second datatypes of Late Iron Age sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red, white, grey, orange), and sex classification of sites. Background © Environment Agency. Natural character areas © Natural England.

Burial Goods per Grave

As potential proxy of social differences, from the Grave Goods project data the average amount of burial goods per grave were determined for each site (fig. 9–14). Traditionally, differences in numbers of objects have been interpreted as proxy of differences in the richness of the graves and, thus, in social status or prestige of the deceased or the bereaved. Even though this line of argument tends to oversimplify the diverse, context-dependent ways graves symbolically communicated meaning (Ekengren, 2013), the potential correlation appears intriguing.

The average amount of grave goods per site was established through the number of graves and objects found at a site. Indeed, there is a strong correlation between most of the different clusters and the amount of graves and objects, which even can be statistically affirmed through an analysis of variance (ANOVA) (cf. tab. 3). Within dataset 1 there is, for example, throughout all periods one cluster consisting solely of sites with single burials (cf. red cluster fig. 9, red cluster fig. 10, and white cluster fig. 11) that can be separated from the other clusters also including sites with multiple burials. Though the number of burials and burial goods apparently influences other aspects of the burial ritual, from a data perspective this seems hardly surprising, as most of the categories used to create the networks (cf. tab. 1 and 2) are more or less directly related to the amount of graves or goods. Contrary to expectations, these potential correlations do not hold true for all datasets. For instance, the amount of objects do not necessarily have a provable influence on the formation of the EBA object-based clusters (dataset 2), as suggested by a probability above a level of significance of 5 %. Looking at the original data, EBA burials are characterised by a great variety of different object materials and types, whose selection for a burial seems to be unrelated to the total amount of the interred objects.

Number of Graves		Number of Grave Goods	
F-score	Probability	F-score	Probability

Dataset 1	EBA	157.370	< 0.001	48.642	< 0.001
	MBA	28.582	< 0.001	10.837	< 0.001
	LIA	8.612	0.002	12.655	< 0.001
Dataset 2	EBA	5.471	0.021	3.607	0.060
	MBA	11.888	< 0.001	17.616	< 0.001
	LIA	1.944	0.147	3.315	0.034

Table 3 – F-scores and probabilities of the analysis of variance of the clusters with the number of graves and grave goods.

On the contrary, for most datasets there is no significant correlation between the average amount of grave goods per grave and the determined clusters (fig. 9–14). One notable exception is the MBA network derived from dataset 1. The network divides the sites into one cluster with more (cf. fig. 13, black cluster) and one with fewer (cf. fig. 13, red cluster) grave goods per grave. As a statistical analysis of variance (ANOVA) revealed, the difference ($F(1,43) = 6.448$, $p = 0.015$) in the amount of burial goods per grave of the black ($M = 3.59$, $SD = 5.82$) and the red cluster ($M = 1.19$, $SD = 0.38$) is statistically significant. Looking at the strength of the network connections, the strongest edges furthermore seem to be located between sites of the black cluster. Yet, during the MBA in Dorset, ceramic vessels used as cremation urns were almost exclusively found as burial goods. Since hardly any other objects are recorded in the MBA graves, it seems rather unlikely that these differences in the average amount of objects should be related to clear social differences. Instead, they rather seem to represent small variations and deviations in an otherwise very uniform grave goods tradition.

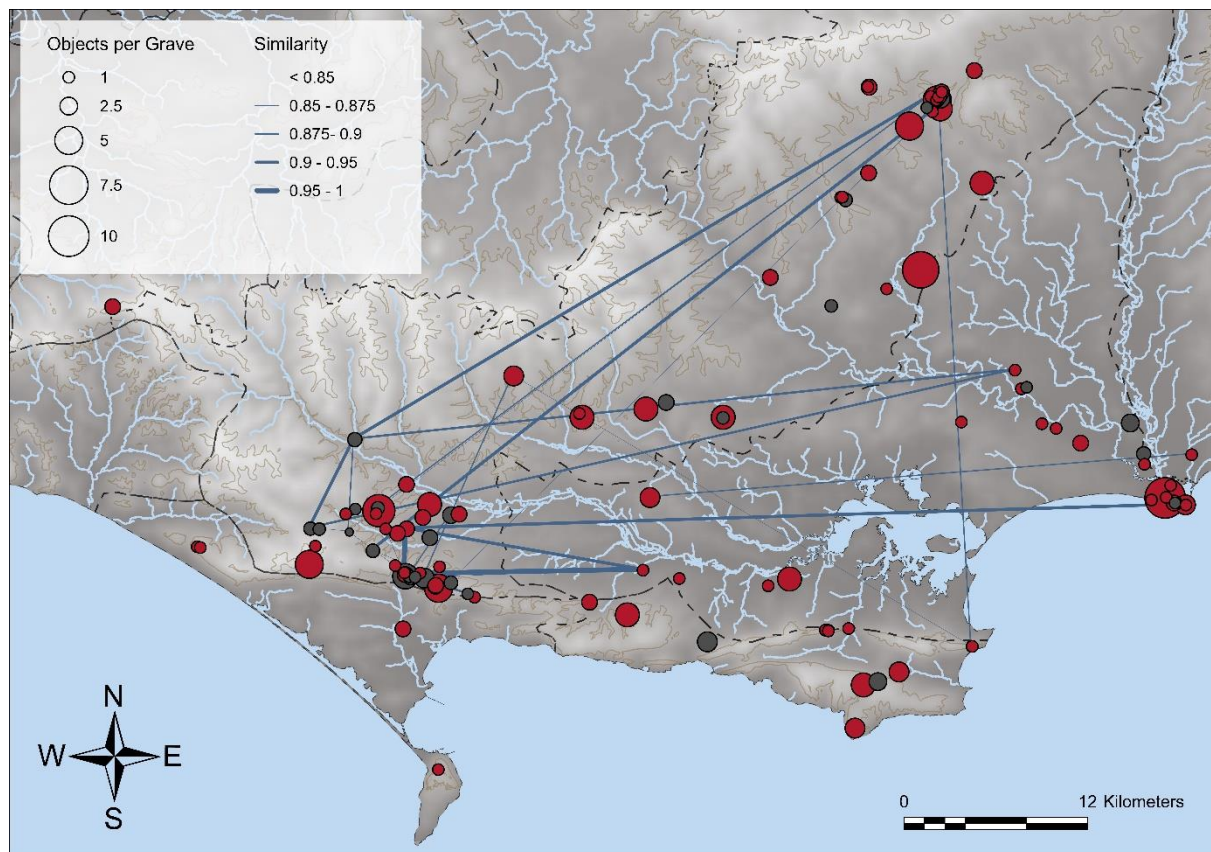


Figure 9 - Similarity network derived from the first datatypes of Early Bronze Age sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red), and average grave goods per grave per site. Background © Environment Agency. Natural character areas © Natural England.

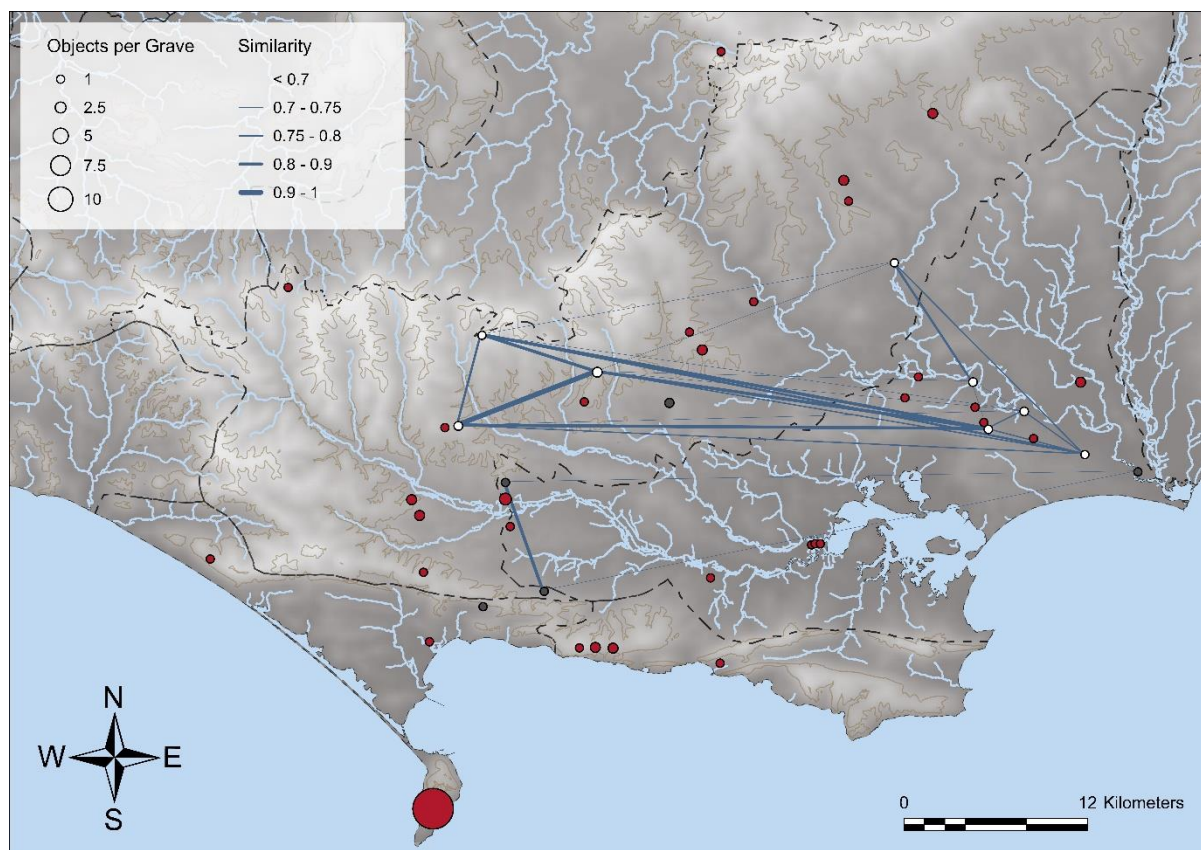


Figure 10 - Similarity network derived from the first datatypes of Middle Bronze Age sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red, white), and average grave goods per grave per site. Background © Environment Agency. Natural character areas © Natural England.

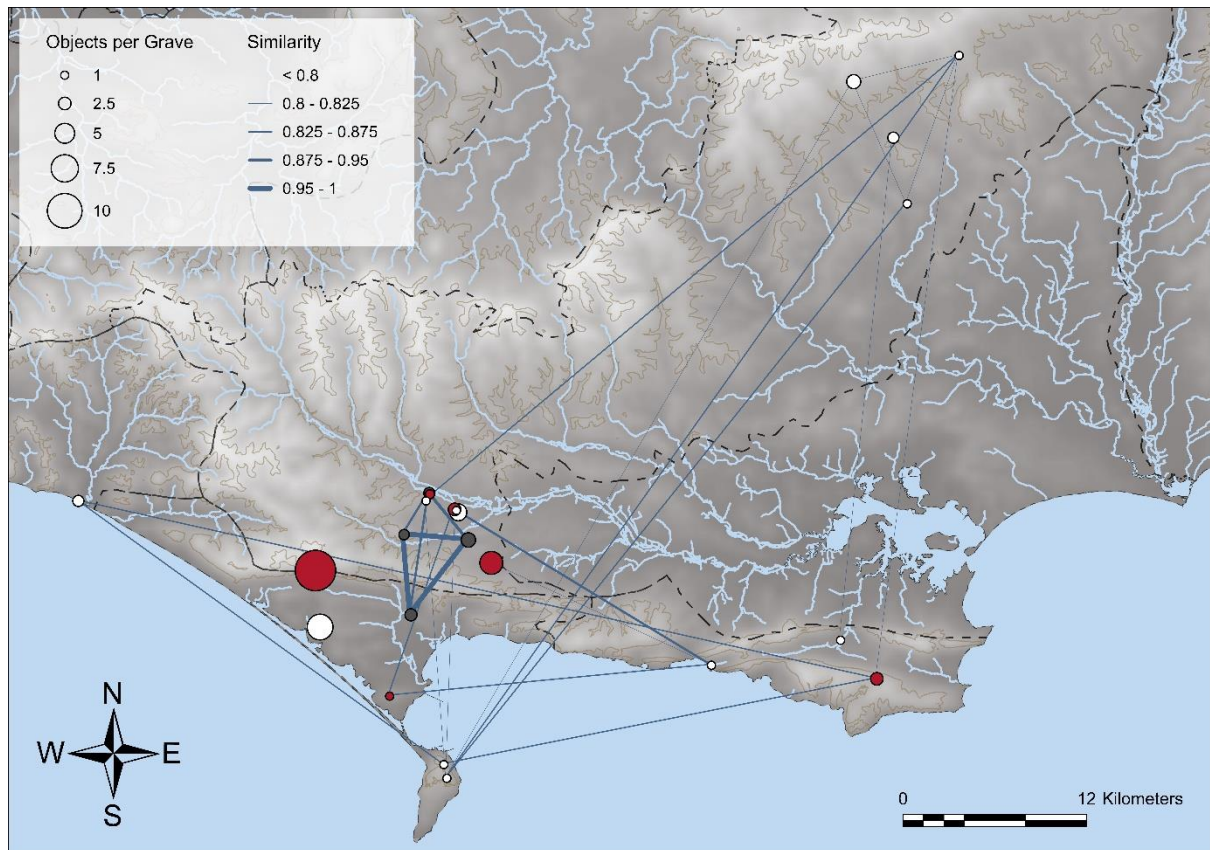


Figure 11 - Similarity network derived from the first datatypes of Late Iron sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red, white), and average grave goods per grave per site. Background © Environment Agency. Natural character areas © Natural England.

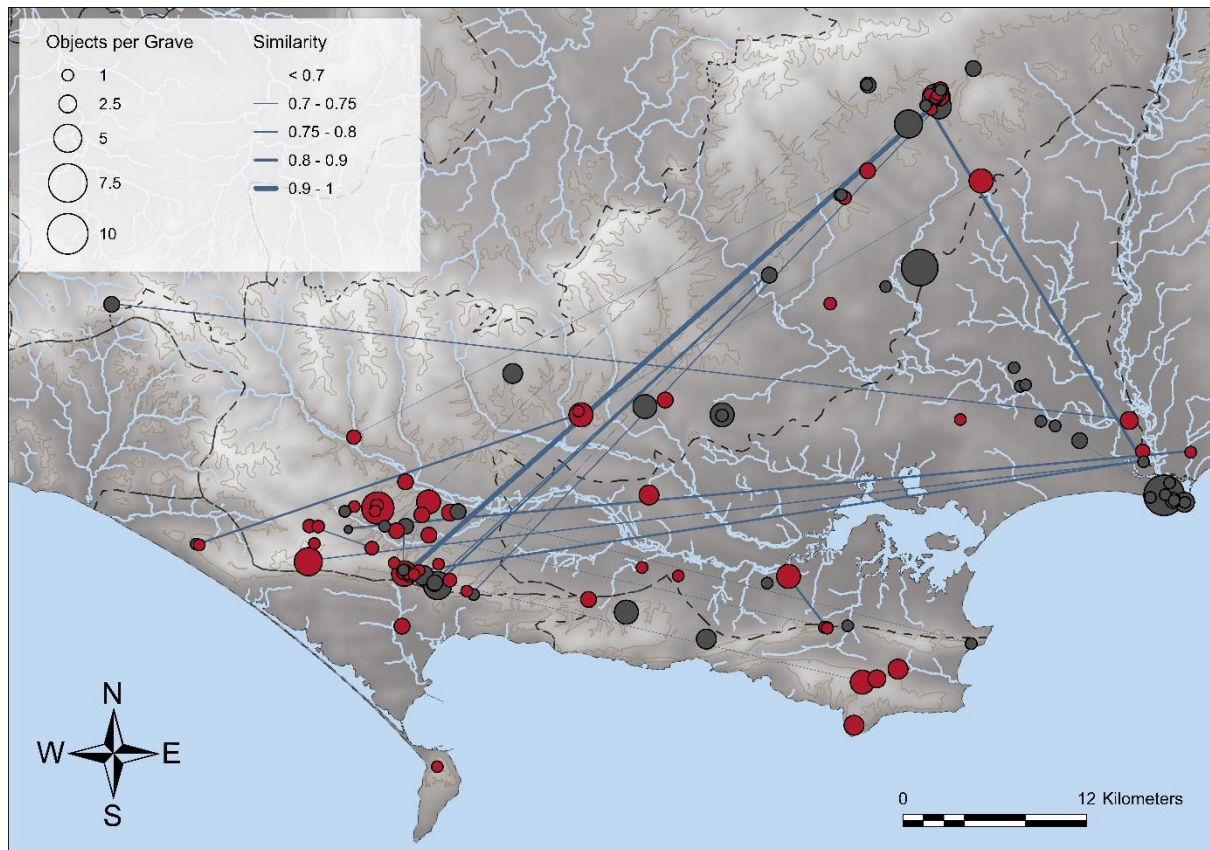


Figure 12 - Similarity network derived from the second datatypes of Early Bronze Age sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red), and average grave goods per grave per site. Background © Environment Agency. Natural character areas © Natural England.

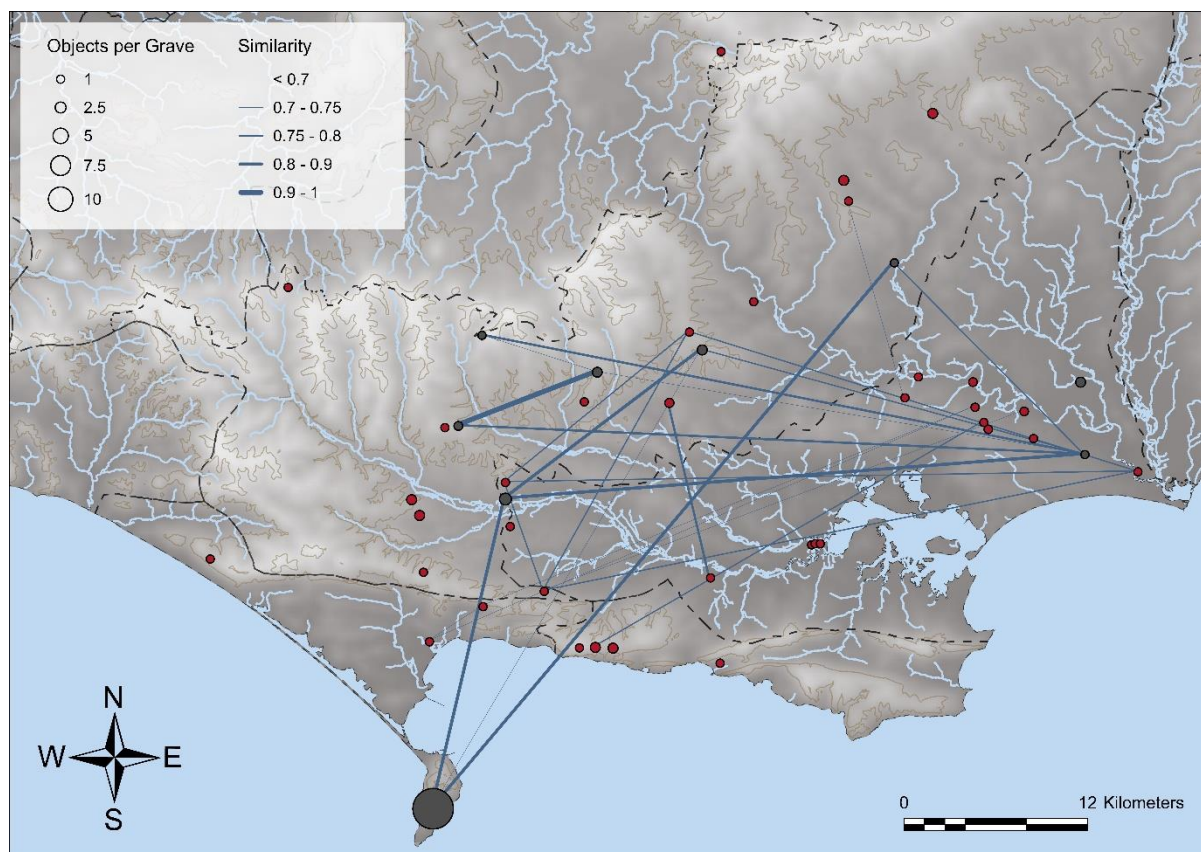


Figure 13 - Similarity network derived from the second datatypes of Middle Bronze Age sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red), and average grave goods per grave per site. Background © Environment Agency. Natural character areas © Natural England.

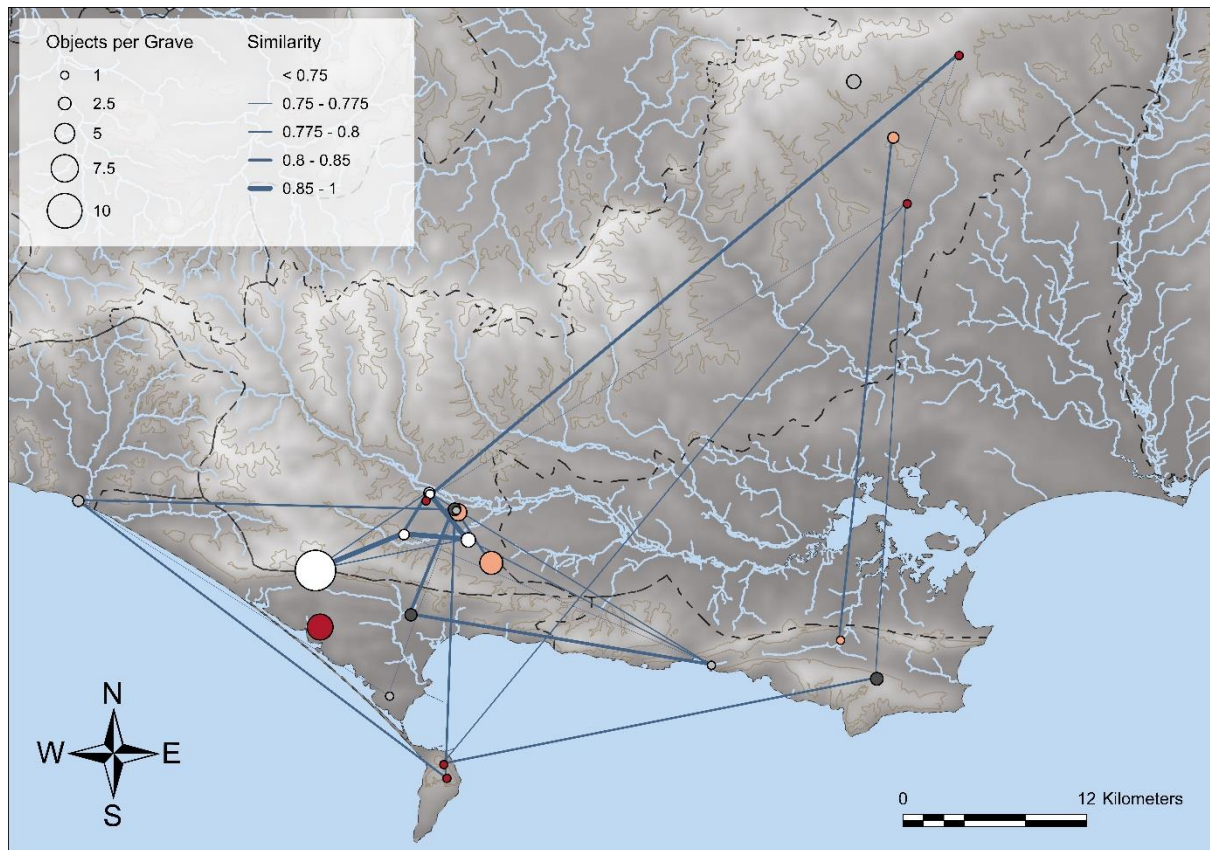


Figure 14 - Similarity network derived from the second datatypes of Late Iron Age sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red, white, grey, orange), and average grave goods per grave per site.

Mover or Local

A differentiation between individuals who were born and died at different locations, thus moved or were moved during or after their lifetime, and individuals who were born and died at the same location, was made on the basis of the isotopic data gathered by the Beaker People Project (Parker Pearson et al., 2019). Though the main focus of the Beaker people project was laid on the Beaker period, during the project abundant of nitrogen, carbon, sulphur, strontium, and oxygen isotope data was sampled and gathered across many time periods and regions. Yet, for EBA, MBA, and LIA Dorset, only individuals from six sites were sampled and could be attributed to the category *local* or *mover*. This sample size is not considered sufficient to make a reasonable statement on potential correlations with network clusters. Nevertheless, even though EBA burials, which make up four of the six samples and consisting of three locals and one mover are evenly distributed across both clusters rather not suggesting any correlation, the ever increasing availability of isotope data might be a promising trajectory to further explore similar patterns in the future.

Chronology

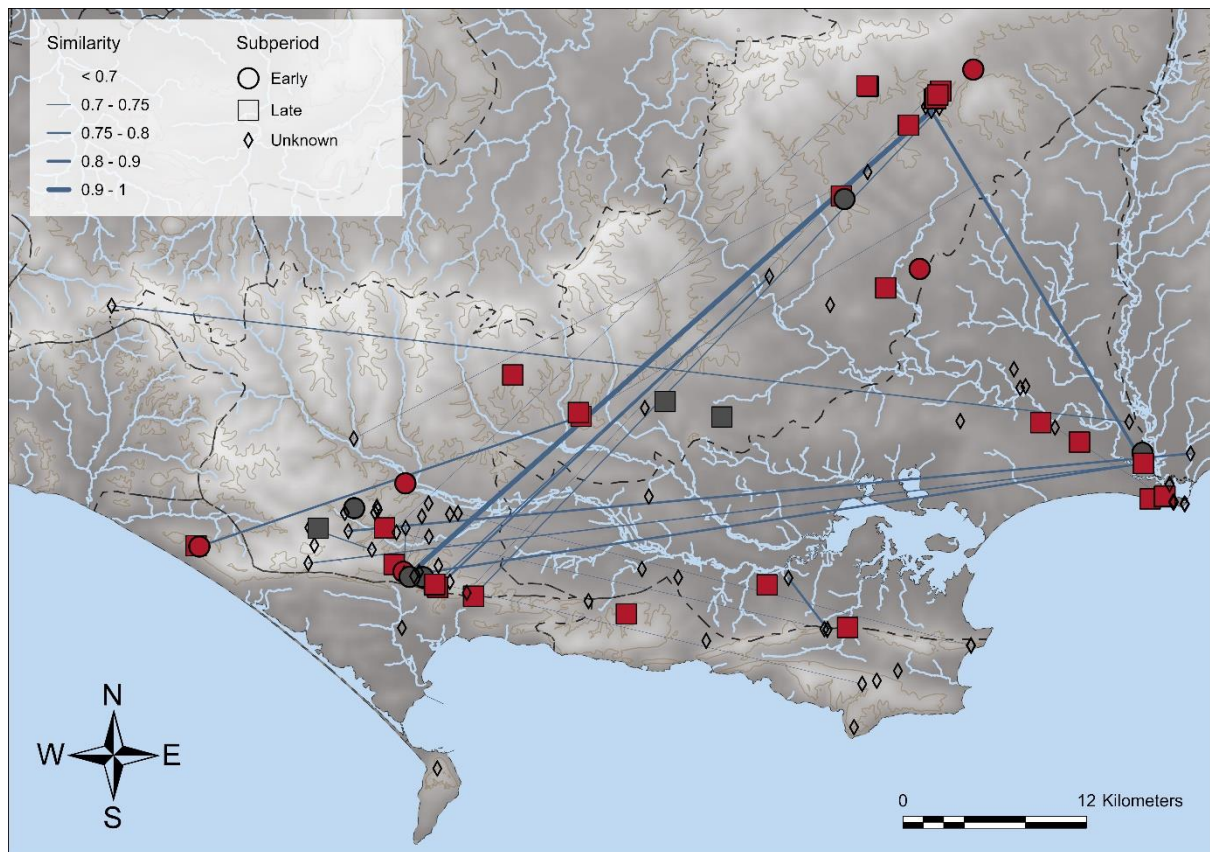


Figure 15 - Similarity network derived from the first datatypes of Early Bronze Age sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red), and sub-period classification. Background © Environment Agency. Natural character areas © Natural England.

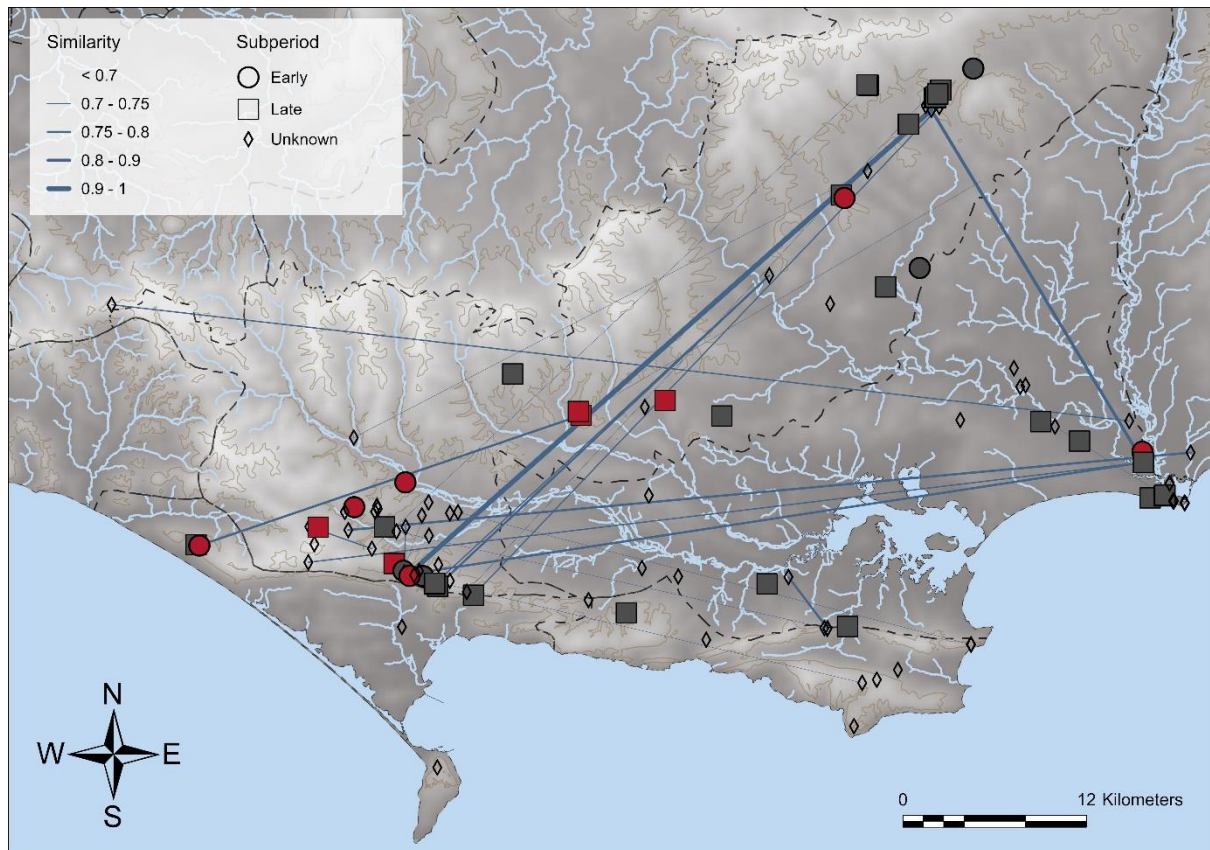


Figure 16 - Similarity network derived from the second datatypes of Early Bronze Age sites in Dorset, depicting the 25 strongest network connections, topological clusters (black, red), and sub-period classification. Background © Environment Agency. Natural character areas © Natural England.

For a set of objects, the Grave Goods project database provides more precise information of the durations of their use. On the supposition that these durations roughly represent the date of their occurrence in burials, these objects were used to refine the period classification of the graves. The refinement of the chronology was solely undertaken for the EBA period, as only for this period the available quantity of information was considered abundant enough. I classified the objects according to whether their duration of occurrence indicated with a greater likelihood that they were used in the early (2200–1900 BCE) or late (1900–1500 BCE) EBA period. By this means, I could differentiate 42 burials in total, consisting of ten early and 32 late EBA graves.

However, the interpretation of a possible correlation of the refined chronological classification with the EBA network clusters does not appear straightforward at all (fig. 15 and 16); superficially, the cluster derived from the network with several aspects of the burial ritual seems to suggest a balanced distribution of early and late EBA burials in the black cluster, while the red cluster appears clearly dominated by the late EBA burials (cf. tab. 4). However, taking into account, that there are three times more burials, which are classified as late EBA, the red cluster appears less significant, while a bias of the black cluster towards early EBA burials seems possible. A similar pattern becomes also apparent for the clusters of the object based network; the black cluster seems even more clearly biased towards late EBA burials, while a dominance of the early EBA burials in the red cluster can only be theorised, by taking the unbalanced nature of the dataset into consideration (cf. tab. 4).

	Early	Late
Total	10	32
Red	5	28
Black	5	4

Table 4 – Association between Dataset 1 of the EBA burials and the sub-period classification.

	Early	Late
Total	10	32
Red	6	6
Black	4	26

Table 4 – Association between Dataset 2 of the EBA burials and the sub-period classification.

An ANOVA defining affiliation with early EBA as 0 and late EBA as 1 revealed that both, the correlation between the first cluster and the classification into early ($M = 0.5, SD = 0.52$) and late ($M = 0.009, SD = 0.3$) EBA ($F(1, 40) = 9.638, p = 0.003$) as well as the correlation between the object cluster and the classification into early ($M = 0.4, SD = 0.52$) and late ($M = 0.81, SD = 0.4$) EBA ($F(1, 40) = 7.128, p = 0.011$) are statistically significant. This correlation is very intriguing, but—especially for the object-derived network—not surprising at all; for relative chronologies or seriation methods, changes in object types are often interpreted as manifestation of time lapse (cf. Ekengren, 2013). If this correlation gets confirmed and refined further, for example through the inclusion of radiocarbon dates, this would open new possibilities, as both spatial and temporal development can be effectively analysed and represented in absolute space.

Conclusion

Material networks are powerful heuristic and analytical tools to understand and visualise relationships between archaeological phenomena. Especially the applied SNF technique proved an effective method for the incorporation of various similarity networks derived from different datatypes into one single network. Moreover, due to its robusticity against small and noisy datasets, this technique also appears to have great potential for other applications and fields in archaeology coping with similar datasets, such as archaeobotany or archaeozoology, and seems to complement other multivariate statistical approaches such as correspondence or cluster analysis.

Many of the typical methodological and interpretive constraints and challenges of network analysis in archaeology also manifest themselves in the discussed case study on late prehistoric burials in Dorset; the area of research could only be inadequately bounded and mainly followed modern borders and the broader data availability. Though for the investigated periods there is a relatively high density of sites across the area of research, the incompleteness and biases of the dataset and their influence on the results of the analysis is unknown. Finally, as past interactions can only be approximated through material culture, the exact meaning of the specific similarity network is difficult to assess and can only indirectly be approached through correlations of different data attributes.

Nevertheless, the network analysis and the topological clustering of the sites revealed at least two possible spatial clusters—within the EBA and LIA networks—and two statistically significant correlations between clusters and further attributes of the burial sites—objects per grave and chronology. The aim of the case study was to shed light on the past landscape and its structuration. Indeed, it seems likely that the distinctions manifesting in the two spatially significant clusters are expressions of diverging cultural behaviour. On the assumption that these differences were conceivable and recognisable in the past, they were contributing to the constiution of the past landscape. The other two statistically significant correlations might have no spatial spatial significance, but as has been argued above they potentially form part of a past social or cultural reality which yet has to be further investigated.

The exploration of the meaning of the topological clusters does not seem to be exhausted by the discussed five attributes; the inclusion of further landscape derived characteristics such as potential trajectories of movement or visibility measures (cf. Woodward, 2000) seems to be particularly promising to understand the spatial location of the topological clusters. Finally, the case study also points to the potential of approaching and re-evaluating freely accessible archaeological data gathered by past research projects with new questions and methods.

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Conflict of interest disclosure

The authors declare that they comply with the PCI rule of having no financial conflicts of interest in relation to the content of the article.

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