Chapter 4
Indicators of Transformation Processes: Change Profiles as a Method for Identifying Indicators

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4.1 Introduction

Societies are in a constant state of change. Archaeological research has shown how some of the driving factors of change in societies include technological innovation, change in subsistence strategies, climate change (e.g. Chap. 6), environmental change, changes in political organisation (e.g. Chap. 9), and population increase or decrease. The list of factors can be extended and detailed at will. However, at what point and in what combination do these factors lead to profound transformations? Recognising and understanding transformation processes is the central research focus of CRC 1266 "Scales of Transformation". Each of the previously mentioned processes may contribute individually to change, but it is their interplay that describes the picture of a profound transformation. Our knowledge on components

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of individual transformation processes is heavily influenced by region-specific chronologies, cultural materials, data availability and research standards. Due to the data variability, and to avoid deterministic approaches, this chapter does not aim to identify a "universally valid set of indicators" of transformation, but rather define a multi-proxy approach based on archaeological aspects, changes in social relations or subsistence, and environmental factors. Analysing singular factors only does not do justice to the complexity of human-environmental interactions. The identification of indicators and their interconnection will ideally permit a better understanding of transformation patterns on a transregional and diachronic scale. In addition to establishing sets of parameters which can be used as indicators of transformation, learning which parameters do not serve as indicators contributes to a much more efficient work flow.

A particularly useful tool for identifying and comparing transformations is change profiles or change plots. Change plots show the degree of change between two phases. This kind of visualisation makes it possible to address the interaction between different parameters and hence it highlights the most relevant ones. Therefore, change profiles might provide us with information about which factors played a significant role in shaping transformations and how the strategies for their integration varied in different (archaeological) contexts. This method is rather easy to apply to different regions and processes and results in a synthetic plot of changing factors. The interpretation has to carefully consider potential natural correlations of different factors that are not entirely independent.

Accordingly, the aim of this chapter is to provide a method not only to visualise interdisciplinary conducted results on transformations, but also to provide a multi-proxy approach for identifying relevant factors in transformational phases using a minimal set of highly available archaeological information. This will not include a full description, or even detection, of *all* transformations, but rather a decent approach for identifying corresponding transformations within different domains. The parameters used comprise geographical key numbers, such as the topographic position index (TPI) and locational preferences, as well as archaeological information, such as site category and the location of specific artefacts such as weapons, imports, and jewellery. Some parameters will show a rather marginal influence but still contribute to a holistic perspective that provides a balance between too simplistic and too complex models. The data sets of this pilot study cover the early Iron Age in South-West Germany and the Iron Age in Central Italy. Especially, for the

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transformation in South-West Germany the interplay of different social, economic and ritual factors is quantified within change profiles. Furthermore, an estimation of the intensity of each transition can be compared to identify those factors most relevant to the transformation.

An important aspect of this approach is the use of publicly available geographical data and the accessibility of the archaeological data used, which ensures not only a certain degree of reproducibility but also the extendibility of this approach. The latter is particularly important, since the present study is a pilot study which aims to trigger additional ones with targeted sets of parameters. These further analyses are intended to include other CRC 1266 projects, as well as completely independent analyses by different authors.

4.1.1 Domains, Parameters and Indicators for Transformations

Transformations are defined here primarily as processes leading to a substantial and enduring re-organisation of socio-environmental interaction patterns, e.g. changed material culture, social relations, settlement patterns or subsistence strategies. A transformation leads to a transformed society that both adapts to new conditions and shapes new conditions. Transformations cannot be reversed because the society has a completely new configuration. Therefore, the continuous change which characterises all communities and societies cannot be considered to be a transformation. Social organisations can adapt gradually to new conditions; societies can collapse and re-emerge with a different shape or undergo transformations that change the internal mechanism of the society. Gradual adaptation has its limitations, it is not only the current political situation that shows that social and political systems tend to preserve themselves and not to transform, if not forced to.

Transformations are embedded in a dynamic process of change between external environmental contexts and internal socio-cultural contexts (cf. Fig. 2.2). These contexts can be assigned to domains, which can range from economy and culture to climate and landscape. Parameters can be assigned to the domains, but they can also be related to each other and cannot be considered as independent variables. Parameters are described by indicators or quantitative proxies. Inequality, for example, can be represented by indicators such as house size, equipment or distribution patterns. However, indicators that are primarily assigned to the parameter of burial rites can also be used as parameters for inequality. Indicators, parameters, and domains form a complicated network of interrelationships and mutual references. Additionally, due to the mutual interference of the factors, a common synchronous representation makes sense in order to be able to circumvent possible duplications in the evaluation. The following examples serve as an illustration of the interconnectedness of the individual factors, parameters and domains.

The parameter climate influences temperature, precipitation, growing season duration of crops and thus also the possible subsistence strategies. Climate has far-reaching influences on agricultural societies, and thus defining independent variables from the parameters of, for example, subsistence, economy, vegetation or hydrology will be difficult. Humans live in, and with, their environment, which is strongly affected by climate. Even in the industrial age, with manifold technical achievements and comprehensive knowledge, societies have to face new problems and conflicts, which are triggered and intensified by the current climate change. Despite the important influence of climate, other relevant factors should not be ignored when interpreting the curves. It is the innovative nature of humans that reduces their dependence on climate. Climate variability is plotted on the synoptic change profiles as a parameter for orientation, but is not included in the analyses.

Settlement patterns can be driven by climatic changes, for example, when the hydrology of the region changes and settlements move closer to bodies of water, or when regions are too dry for arable provisioning of the community. The factors to be derived from this, such as proximity to water, elevation (TPI, aspect, etc.) can be derived from the location, categorisation, and dating of sites in combination with digital elevation models. A critical analysis of the source situation should precede, especially when considering distance to water and other settlements, as missing settlements or imprecise dating can have a significant impact on the results.

The social domain of settlement systems, on the other hand, such as even distribution within a region versus the clustering of settlements, can be considered as detached from climate. However, caution must still be taken in the interpretation here, and the inherent limitations of the method and alternative explanatory models must be examined.

Other social markers can be extracted from burial rites. The number and size of burial mounds or cemeteries, the number of "status symbols" in graves (weapons, chariots, ornamental vessels, jewellery), or even changes in burial rite (e.g. the change from inhumation to cremation graves) can be interpreted as effects of social change in a change profile. Changes in the ritual sphere of a society can also be seen, for example, from a change in burial rite and the associated change in world-view (*Weltanschauung*). The shift to inhumation, together with the abandonment of the hoard tradition and of sun iconography, at the beginning of the Early Iron Age can be seen as an expression of a fundamentally changed world-view and conception of the afterlife (Rebay-Salisbury, 2017). However, an additional political aspect cannot be excluded, especially at the beginning of the early Iron Age, because the so-called elites first accepted the new ideological world-view, before it became generally accepted by the whole population (Faupel, 2021; Tremblay Cormier, 2017).

4.2 Archaeological Case Studies

With the selection of the case studies, two quite contrasting cases are considered. In one case, little additional data is available besides the categorisation and dating of the site; therefore, the first step is to begin analysing the site parameters and then, if possible, to add further research results at a later stage. The second case study has numerous additional data from a very detailed data collection of an earlier project (http://landman-neu.sfb1266.uni-kiel.de/landman/repository/24/). The comparison of these two case studies is intended to show the feasibility of transformation research with change profiles and location-based indicators. Furthermore, in both cases a phase with well-known transformation has been chosen; these transformations take place almost at the same time, but in very different geographical settings.

The Early Iron Age in Baden-Württemberg represents a well-known transformation of society – which includes the emergence and rise of certain elites, visible in prestige graves and princely seats in the Hallstatt period, followed by a process sometimes called democratisation, in the Latène period – and is a perfect test case for the parameters focusing on settlement location. The second case study of Etruria partly covers the same period but has completely different history, with the emergence of city states, their competition, and the end of a balanced political system by the Roman occupation.

4.2.1 Baden-Württemberg

Ostentatious burial mounds, rich grave goods, and princely seats with exotic Mediterranean imports describe the picture of the early Iron Age in southwestern Germany and the Alsace. With the beginning of the Iron Age, a new epoch seems to have dawned, which led to a change in the form of settlement, brought new materials and thus new markets with it, as well as introduced a new burial custom. At first sight, this new cultural phenomenon has an enormous spread and extends – divided into the western and eastern Hallstatt areas – over almost all of Central Europe. However, if one takes a closer look at the material culture, the settlement pattern and the burial rites, this cultural entity is divided into numerous small regional groups. Studies have clearly shown that the heterogeneity of the cultural groups is predominant (Nakoinz, 2013; Parzinger, 1991). The commonalities are induced by an elite that apparently shared a comparable symbolism of their power (Tremblay Cormier, 2017).

The transition from the Late Bronze Age to the Early Iron Age is not recognisable in the archaeological material as an abrupt change. The introduction of the new material, iron, is also slightly delayed in relation to the social changes already discussed. The fact that the typology of numerous artefacts develops continuously from the Bronze Age into the Iron Age is a clear indication of changes within a domain. The accumulation of these changes, especially the changed settlement patterns and possibly new social structure, combined with climatic changes (Billamboz, 2007; Milcent, 2009) led to a transformation process.

Even though the end of the Early Iron Age is chronologically more precise than the beginning, the possible reasons for the collapse of the Hallstatt culture are not fully understood. Climatic deterioration, migratory movements (Celtic migration), and centres of power shifting northward are possible explanations (Brun, 1995; Fernández-Götz, 2018; Maise, 1996; Tomaschitz, 2002). Recognisable changes include a drastic reduction in population and the collapse of central places, such as the so-called princely seats. The settlement pattern in the following epoch is characterised by a very decentralised settlement pattern (Fernández-Götz, 2018).

Accordingly, by considering the Early Iron Age in Baden-Württemberg, two transformation horizons are considered: on the one hand, the change from the Bronze Age to the Iron Age and, on the other hand, the transition of the Hallstatt Period to the Latène Period. The fact that profound changes in society occurred during these periods is evident in the analysis of material culture, but it remains unclear which factors are relevant in this phase of change and which are possibly "only" clear detectable archaeologically.

4.2.2 Etruria

The region of Etruria is commonly identified as the area between the Arno and Tiber rivers, with its eastern borders defined by the mountainous chain of the Apennines. Here, several urban centres rose to prosperity during the first millennium BCE, each characterised by their own cultural identities and political institutions, (Haynes, 2000), but united by a sense of belonging to the same ethnic identity.

The study of material culture, especially of aristocratic funerary contexts, highlighted these aspects, but were often approached from an antiquarian point of view, and therefore stripped of their social and cultural context (Izzet, 2007, p. 16). Further impediments are the limited data coming from urban contexts, as these ancient cities have either been severely damaged by erosion or by reoccupation. Moreover, the texts and language of the Etruscans are limited in number, as well as in their comprehension: the majority of the information comes from foreign sources (Greek and Roman), who had the habit of reporting the Etruscans as fun-loving but lewd people. Because of such scant and biased information, landscape studies from numerous twentieth-century surveys and excavation projects become vital for the study of a civilisation that has its roots deep in the Bronze Age and that developed over a millennium, going through several 'transformations'.

And 'transformation' is indeed the characterising quality of Etruria. Several stages can be highlighted, from the occupation of open sites in the Middle Bronze Age, to their abandonment by the tenth century BCE, and the choice to relocate large portions of the population on naturally defensible locations (Peroni, 1989). From the tenth to the eighth centuries BCE, the largest plateaus, where available, were preferred for the establishment of large centres, while a good portion of the earlier, smaller sites were abandoned. Clusters of villages formed, initiating a major process of nucleation and a radical change in value system and political development, all of which was particularly visible in the new warrior ideology present in the cremation cemeteries that rose around them. This new cultural manifestation is referred to as the 'Villanovan' period, with sparks of what will be characteristic for the fully urbanised Etruscan period (Stoddart, 2016). These include the emergence of lineages and elites, the acquisition of resources, and the mitigation of conflicts by promoting the stability of centralised polities (Terrenato, 2011, 2020). These pull factors are completed in the following centuries, from the eighth century BCE onwards, when centralisation was accompanied by gradual craft-specialisation and social differentiation, as well as technological development. These transformations are represented by large tumuli that surround the now-urbanised plateaus, as well as the countryside, characterised by rich deposits showing the integration within eastern Mediterranean trade networks (Bartoloni, 2012, p. 103). In this period, Etruscan centres become forces to be reckoned with, some establishing their primacy on the sea, as well as on the Italian peninsula, through the control of resources, trade routes and the foundation of colonies. Conflicts must have characterised relations not only with external players (Greeks and later Romans) but also among the cities themselves, as the destruction of minor frontier minor settlements such as Acquarossa and Murlo and the foundation of a league of Etruscan cities can indicate (Stoddart, 2020). Parallel to this, the previously emptied landscape underwent a massive repopulation, with the development of complex settlement hierarchies sustaining such growth.

These major developments affected Etruria at different rates and at different times: southern centres became prominent in the early phase of Etruscan development, while northern centres emerged unchallenged when southern Etruria declined from the fifth century BCE. After the loss of international supremacy with the battle of Cumae (474 BCE), these southern centres had to deal with the aggressive political agenda of a new and determinant factor of transformation: Rome. One by one the cities fell or joined Rome, Veii being the first, and colonies were founded. Northern centres, on the other hand, opted for a different strategy – one of collaboration –, seeking political advantages, as is evident once again from the rural data and the funerary evidence. Etruria was severely punished during the Marius/Sulla conflict for siding with the loser (Torelli, 1990). It was dismantled in 27 BCE, when a new phase of its history started, one that saw it officially as part of Roman Italy, becoming its seventh region, with the disappearance of the Etruscan language and the adoption of Latin (Haynes, 2000, pp. 385–386).

4.3 Data

Comparable datasets of specific, known transformational phases are rarely available. Regions differ not only in their individual geography and associated vegetation, climate, and possible subsistence strategies, but also in their source material. Additionally, differences refer not only to archaeological source filters, but also to the presence of palaeoenvironmental archives, as well as current research status. Even within the CRC 1266, which investigates various transformations, it is not always possible to obtain a good, directly comparable database. The categorising, dating, and localisation of a site can serve as the smallest common denominator, although there are limits here; for example, the dating accuracy. If one accepts a certain degree of inaccuracy, which usually describes the archaeological reality, these three fundamental aspects about a site can be compared to some extent. However, the inaccuracy must be taken into account when interpreting the results. By evaluating location parameters, a comparative study can be carried out, which can be supported by additional data if necessary. In addition, depending on the epoch, research question, and data availability, additional data might cover other social and political factors, such as a known settlement hierarchy, prestigious graves, the number and distribution of imported goods, central buildings, or signs of social group affiliations.

4.3.1 Geographical Data

Modern digital elevation models are used for evaluating parameters of the location of a given site. Whether modern data can be used to study past changes in parameters depends on the degree of change in landscape and the likelihood of preserved archaeological features. The continuous transformation of landscapes is well known (Gerlach, 2003; Kvamme, 2006). Whether it is erosion induced by climate or changes caused by anthropogenic land use, the speed and extent of change are relevant. Knitter et al. (2019) compared the duration of the existence of landforms with that of monuments from a Neolithic case study to demonstrate the applicability of modern terrain models. Valleys or isolated hills exist for a period of between 1000 and 10,000 years (Ahnert, 1981), while more pronounced landforms endure for even longer periods. The epochs under consideration here are about 3000 years old, so the modern surface can be considered comparable.

Nevertheless, during the past two centuries, there have been notable changes in the landscape. These anthropogenic influences, such as building activities, raw material extraction, channelling of rivers, and reallocation of agricultural lands after World War II, do not change the geomorphological trend of a landscape (Herzog, 2014; Herzog & Posluschny, 2011; Kvamme, 2006; Mischka, 2007; Sauerbier et al., 2006).

The present analysis of the geographical data is designed for a regional comparison, which is why a DEM with a resolution of 90 m (SRTM of 3-arc-second[1]) was chosen. This provides a sufficiently precise representation of the landscape without being overly influenced by modern structures (such as highways). The R-Package *geodata* (Hijmans et al., 2023) was used to download the SRTM 3 digital elevation model, the global administrative boundaries (GADM) and the soil data for the area of the case study in Baden-Württemberg. Afterwards, the package *terra* (Hijmans, 2023) was used for calculating derived data, such as slope and aspect. The soil data (ISRIC, 2021, https://www.isric.org/explore/soilgrids) are from 15–30 cm depth

[1] Generally, accuracy for SRTM-C band data (90% confidence intervals are 8.8 m absolute geolocation error and a 6.2 m absolute elevation error: Rodriguez et al., 2005).

and cover nitrogen (total nitrogen (N) g/kg), pH (pH (H_2O)), sand (>0.05 mm, in fine earth %) and clay (<0.002 mm, in fine earth %).

4.3.2 Climate Data

The climate data originate from transient model simulations of the Earth System Model from the Max Planck Institute for Meteorology (MPI-ESM, version 1.2: Mauritsen et al., 2019; cf. also Mikolajewicz et al., 2018). The model consists of the spectral atmosphere general circulation model ECHAM6.3 (Stevens et al., 2013), the land surface vegetation model JSBACH3.2 (Raddatz et al., 2007), and the primitive equation ocean model MPIOM1.6 (Marsland et al., 2003). In this set-up, the atmospheric component ECHAM6.3 has a T31 horizontal resolution (approx. 3.75°) with 31 vertical hybrid s-levels which resolve the atmosphere up to 0.01 hPa (Stevens et al., 2013). The ocean component, MPIOM1.6, has a nominal resolution of 3° with two poles located over Greenland and Antarctica (Mikolajewicz et al., 2007). The Earth System Model was started from a spun-up glacial steady state and integrated from 26 ka until the year 1950 with prescribed atmospheric greenhouse gases (Köhler et al., 2017) and insolation (Berger & Loutre, 1991). Volcanoes are not included. The ice sheets and surface topographies were prescribed from the GLAC-1D (Briggs et al., 2014; Tarasov et al., 2012) reconstructions (Kageyama et al., 2017, see standardised PMIP4 experiments). The topography varies with time (Meccia & Mikolajewicz, 2018) and river routing (Riddick et al., 2018). We focus our analysis on simulated temperature and precipitation with a time resolution of 100-year averages during the last 10 ka of the simulation.

The reference model refers to the version described in Kapsch et al. (2021, run 212). To assess the model uncertainties, this reference model simulation is compared to additional simulations based on another ice sheet product (ice6-g: Peltier et al., 2012) and a slightly changed cloud parametrisation. By combining these modifications, four model simulations are used in total.

The climate models for both case studies are aligned with an archaeological chronology. Therefore, variation in temperature (average, summer, and winter) and precipitation is depicted in dates BCE (see Figs. 4.1 and 4.2). Although climate variation will be plotted in the change profiles of the given transformational phases, climate is not assumed to be the sole trigger of transformation. Nevertheless, climatic variation is important to highlight changes in specific domains, and serves as orientation in change profiles.

The average temperature rises at the beginning of the Hallstatt period in Baden-Württemberg, with a maximum around 650 BCE. During the Hallstatt period a minimum average temperature occurs around 350 BCE. The variation in temperature becomes more prominent when considering the average temperature curves for summer versus winter seasons.

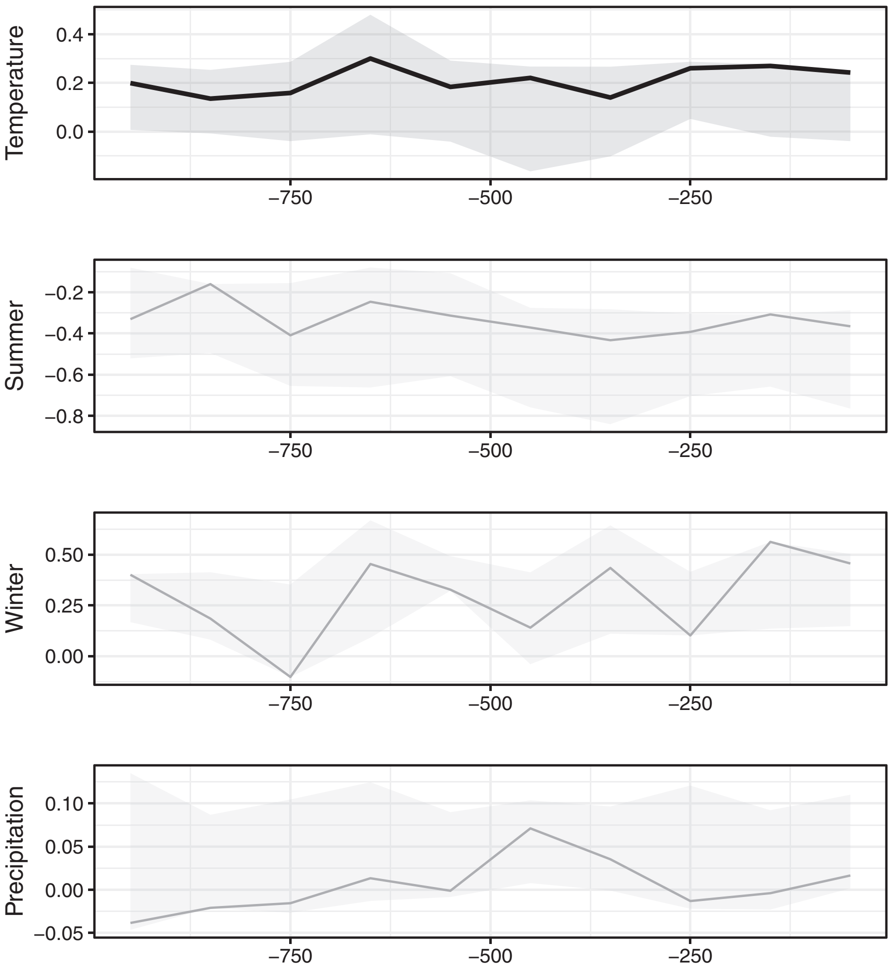

Fig. 4.1 Climate variation during the Early Iron Age in Baden-Württemberg

Similar to climate curves in Baden-Württemberg, a rising average temperature can also be observed at 650 BCE in Etruria; however, the average temperature does not drop as drastically as in Baden-Württemberg (Fig. 4.2).

4.3.3 Archaeological Data

For the present analysis, an existing data collection was used, which lists the locations of the early Iron Age in Baden-Württemberg with coordinates, datings and, if available, archaeological finds. The database (SHKR: Krauße et al., 2013; cf. also Faupel, 2021; Nakoinz, 2013; http://landman-neu.sfb1266.uni-kiel.de/landman/

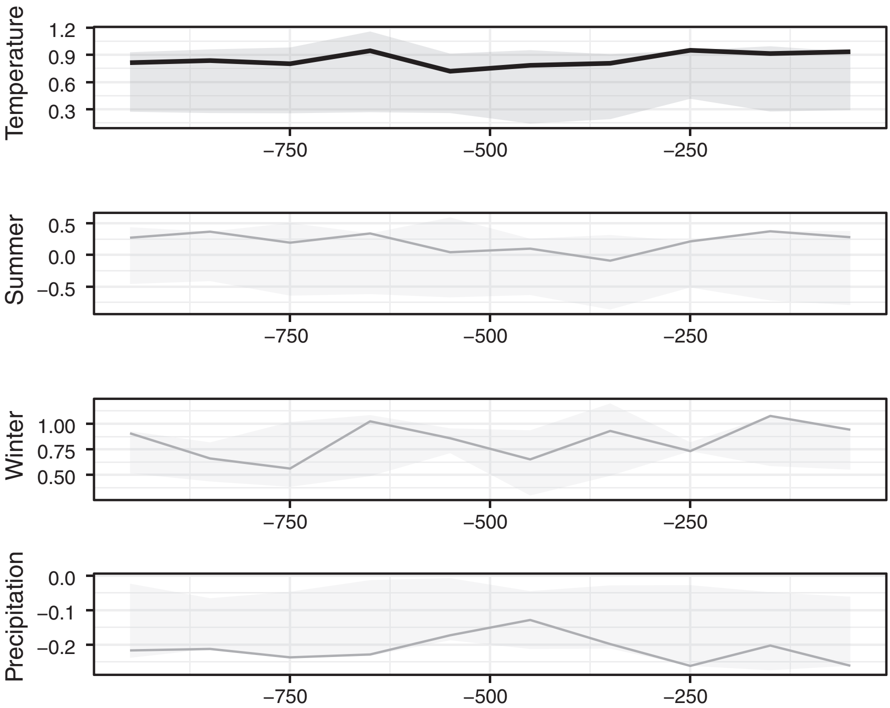

Fig. 4.2 Climate Variability for Etruria during the Iron Age

Table 4.1 Site numbers for case study in Baden-Württemberg

Phase	Counts
Ha C + Ha D	1019
Hallstatt period (Ha)	2137
Early Latène period (FLT)	505
Iron age (EZ)	2901
undated	8170

repository/24/) contains 7954 graves and 2353 settlements. The graves include undated burial mounds that very likely date to the Iron Age (see Table 4.1).

According to the variable precision of dating (Table 4.2), the number of sites decreases with increasing dating precision. This accounts for the fact that the sum of Ha C and Ha D sites does not match the number of Ha sites (Table 4.1), although the Hallstatt period is supposed to comprise Ha C and Ha D only, while Ha A and B are Bronze Age.

Due to the methodological focus of this chapter, we are using the phases Ha C, Ha D and Early Latène (= Lt A and Lt B). Hallstatt (= Ha C and Ha D) is considered for comparison, as mentioned above, and the chronological subphases such as Ha D2 are not taken into consideration for this chapter; though in the future they need to be considered in order to obtain detailed knowledge on all transformations.

Table 4.2 Chronology for Baden-Württemberg

Name_ short	Name_long	Plotname	Start (BCE)	End (BCE)	Centre (BCE)	Duration (in years)
Ha	Hallstatt period	Ha C-D	−800	−450	−625	350
Ha C	Hallstatt C period	Ha C	−800	−620	−710	180
Ha D	Hallstatt D period	Ha D	−620	−450	−535	170
FLT	Early Latène period	Lt A-B	−450	−250	−350	200

Table 4.3 Type of sites for case study in Baden-Württemberg

Phase	Graves	Settlements
Hallstatt C period (Ha C)	161	91
Hallstatt D period (Ha D)	537	250
Hallstatt period (Ha)	909	1147
Early Latène period (FLT)	234	296

Table 4.4 Chronology and sites for Etruria

Phase names	Start (BCE)	End (BCE)	Centre (BCE)	Duration (in years)	Sites
Iron Age	−1000	−730	−865	270	71
Orientalising Phase	−730	−580	−655	150	286
Archaic Phase	−580	−470	−525	110	957
Classical Phase	−470	−330	−400	140	643
Hellenistic Phase	−330	−30	−180	300	2354

The two categories of sources, graves and settlements, are distributed differently (see Table 4.3), so that source filters can be deduced. Hence, both categories are analysed separately. This makes six datasets to analyse in total: graves Ha C, graves Ha D, graves Early Latène, settlements Ha C, settlements Ha D and settlements Early Latène. Accordingly, these datasets cover two transformations: Ha C to Ha D, and Ha D to Early Latène.

The archaeological data for the case study in Etruria are based on the Palmisano et al. (2017) data collection (see Table 4.4 for the used chronology and sites).

4.4 Methodology

Before describing the methods in detail, a rough sketch will be given in order to provide an orientation in the methods section. This chapter aims to explore the use of rather simple and widely applicable transformation indicators. For this purpose, we focus on rather well-known transformations and use only the location-based indicators for these transformations. Although the Iron Age transformations used in this chapter are rather well known, sound quantitative approximations of the intensity of change are not available for these transformations. Hence, a simple validation of the results of our indicators is not possible, and we have to turn to hermeneutic evaluations of the indicators which compare the different Iron Age transformations and this involves additional information.

The first step is to define indicators. For this purpose, we develop simple characteristic numbers for the different phases that aim to use natural units and are normalised; for example, based on point pattern analysis. These numbers are used to calculate the factor of change between the phases. In addition, some indices provide change factors directly, since no single characteristic number for the phases is involved.

The next step is to explore the interrelationship of the provided indicators, for which we assume a certain degree of correlation. A principal component analysis (PCA) serves the purpose of a first exploration and visualisation. In the next step, a certain correlation threshold is used to define clusters of indicators, one of which is selected as representative of each cluster. This approach reduced the number of indicators considerably without reducing the information the indicators cover too much. The visualisation of these remaining indicators with change profiles provides us with a basis for evaluating the predictive power of the indicators. Finally, the location indicators are compared and discussed with other information as hermeneutic evaluation.

4.4.1 Point Pattern Analysis

This study applies different methods that are concerned with the location of sites. The conceptual background is formed by the so-called first-order and second-order point pattern analysis (PPA). While first-order analysis is focused on the environmental parameters that determine a site location, second-order analysis investigates the relationship of sites to other sites. Hence, first-order analysis focuses on economic aspects, while second-order analysis focuses rather on social aspects at a certain level.

Based on the first and second order analysis, transformation indicators are then defined. These indicators are presented with diachronic change profiles. The diachronic change profiles have the purpose of comparing the results of the individual cases. This allows us to estimate the degree of changes. Furthermore, the comparison is much more methodologically robust than the estimation of particular point pattern types.

Finally, correlation analysis and principal component analysis serve the purpose of validating the set of indicators and identifying redundant variables. With these methods we will answer the question of which minimum set of indicators is required to characterise a transformation from the perspective of settlement patterns.

4.4.1.1 Identifying First-Order Effects

First-order effects of PPA are estimates of a point pattern with regard to underlying or explanatory covariates, most likely environmental parameters such as topographic features, geomorphological conditions, or the distance and access to fresh water deriving from hydrologic systems. Inherent in such an approach is the rather deterministic assumption that particular environmental features in the landscape are more attractive than others, and that there are environmental factors that control human behaviour. Depending on the type of archaeological record (e.g. settlement or graveyard), attraction and rejection in the moment of human-environment interaction can be – at least theoretically – traced through the manifestation of the record itself as a function of the explanatory covariates. Eventually, and considering large archaeological site databases, this produces an estimate of preference or avoidance of particular landscape features during specific chronological periods and further allows tracing differences among groups, time-slices, or geographic areas.

Furthermore, the approach presented in this chapter enables us to track site location parameters not only as a spatially static component in human decision-making; it also integrates a catchment composition evaluation in the analysis. Using continuous data, for example from slope gradient generated using the DEM, preferences for particular slope ranges, and thus topographic roughness, can be estimated. In addition, a focal approach can be applied that aims at testing the composition of particular environmental conditions within a predefined complementary region. This has the advantage that, for example, when using a soil database not only the environmental conditions at a specific site (here a point, which can be considered at best two-dimensional) are taken into account, but also the variation of these conditions within the catchment; in this case, different soil types with different suitability for crop cultivation, as pastures, or for settlement purposes.

The terrain characteristic is calculated with the function *terrain* from the terra package (Hijmans, 2023) based on the srtm3 digital elevation model (CIGAR-CSI: Jarvis et al., 2008). Slope, aspect, TPI (Topographic Position Index), TRI (Terrain Ruggedness Index), and roughness are used.

4.4.1.2 Identifying Second-Order Effects

The second order effects (Baddeley et al., 2015; Nakoinz & Knitter, 2016; Ripley, 1981) focus on the interaction between sites: do they reject or attract new ones? Or is there no interaction at all? At a point pattern level, the question is whether existing points determine the location of new ones. At a data level, we are turning from the relationship of the sites to other kinds of data, to the relationship inside the site dataset itself. The reflective nature of the methods discussed here accounts for the name 'second-order point pattern analysis'.

The traditional approach of second-order point pattern analysis is to test whether a point pattern could be the result of a random point process, specifically a Poisson process. Defining squares and comparing the counted points to the point number estimated by a theoretical process has the disadvantage of arbitrary squares influencing the result. Ripley (1981), hence, suggested distance-based methods he called field methods. The basic idea is to look at the distances between points and calculate the accumulated numbers up to a threshold that serves as an independent variable of the curve. If the curve of the empirical point pattern matches the one of the theoretical random point process, interaction cannot be assumed. Due to the problem of estimating how far apart the two curves can be while still assuming randomness, simulations are used. The upper and lower limits of the simulations of random processes are indicated in the graphs. Randomness is rejected if the empirical curve is outside this area.

Ripley (1981) defined different types of curves according to the consideration of different pairs of points. The nearest neighbour function or G-function considers the nearest neighbours of each point only. If the empirical curve is above the theoretical one for random processes, more shorter connections than expected exist and hence, clustered point pattern is expected. The probability of a next point being nearby is rather high due to the concentration of the points in a certain cluster. Accordingly, an empirical curve below the theoretical one indicates a regular pattern because the points are spaced with rather maximal distances.

The empty space function or G-function uses a simulated set of random points that connect to the nearest data point. The interpretation is inverse because the likelihood of a simulated point of having a data point nearby is rather low for clusters, since the simulated points are not concentrated in the same area as the data points. An empirical curve below the theoretical one shows more large distances from the random points to the data points than expected.

Finally, the K-function has to be mentioned. This function works similarly to the G-function but does not consider only the nearest neighbour. For this reason, the K-function is considered rather robust but not very sensitive to specific patterns. The G- and F-function in particular have a specific sensitivity. The G-function can be said to take a perspective from inside the pattern because each data point provides a starting point for a connection, and hence a perspective on the pattern. Low density areas and the overarching organisation of clusters are blind spots in this approach, while the F-function focuses on exactly these aspects. Accordingly, the different functions complement each other and one function alone is not able to produce a decent description of a point pattern.

The second-order point pattern analysis can be considered to represent the social aspect of landscape archaeological research because it focuses on the relationship of sites. This type of analysis cannot reveal details of the relationship between different communities, but simplifies rather complex relationships to an estimation of intended intensity of interaction between the sites. This approach has two weaknesses. First, either first-order effects are excluded completely or they need to be included into the analysis by making them part of the simulation of the theoretical point patterns. Both alternatives are rather unrealistic in archaeology. Second, the theoretical models usually used in the analysis are meaningless in archaeology. It would require specific archaeological point pattern simulations instead of Poisson processes to gain meaningful knowledge. These points would question the application of second-order point pattern analysis in archaeology if a simple solution were not at hand. This solution is to not interpret the results directly, but to compare the results of different phases and regions. In this way, the influence of the first-order effects and of the theoretical model are minimised.

For this purpose, the curves need to be transformed to single numbers. With this additional simplification we lose further information but the basic characteristics of the point patterns are still preserved. Since we do not need the theoretical model to answer a question concerning the nature of the point pattern, but rather to characterise the point pattern, we can just use the theoretical curve as a base line and subtract it from the empirical one. Subsequently, the mean value of the sample points of the curve can be calculated. This number has a different meaning than just using the mean of the distances used for the curve, because the curves are mapping frequencies not distances. This leads us to a final simplification. Though the meaning of the index developed in the aforementioned process is different from an index based on the mean nearest neighbour distance, this difference is not that relevant for the comparison of different phases. Finally, we reach very simple second-order point pattern indicators that are based on the nearest neighbour distances and that are justified by the reasoning above. With this tool at hand we are able to compare different phases quite easily.

4.4.2 Identification of Indicators

Technically, we can distinguish three cases due to the kind of data used for the characterisation of the transformations and the phases.

1. **num**: Each settlement pattern is characterised by a specific number. Two point patterns can be compared by the difference of the characteristic numbers divided by the characteristic number of the first point pattern. This number represents the relative change.
2. **vec**: Each settlement pattern is characterised by a specific vector or set of numbers such as the number of sites at certain altitude ranges. These spectra allow us to calculate distances between the point patterns. For this purpose, we are using the Manhattan distance because each variable is scaled in the same way, but the variables need not establish a meaningful space in which the Euclidean distance would make sense. The distances can be scales comparable with the other indices.
3. **mat**: Each settlement pattern is characterised by a specific matrix or complex set of numbers, such as density distribution of two settlement patterns. In this case, a specific function (e.g. the displacement score) is used to describe the relationship of the two settlement patterns.

Though the change profiles would be the preferred place to compare two settlement patterns from two phases, for all three cases transformation indices are calculated for the sake of coherence and comparison.

In the case of vectors of characteristic value spectra, the values are normalised to fit the interval between 0 and 1, and twelve categories are defined. The observations of each category are calculated with the histogram function, and hence this indicator type is indicated with "hist" as part of its name. We have to distinguish two perspectives on the transformations. First, the values can change and this transformation aspect is covered by the distance between the two point patterns. In this case the diversity of values might be preserved. As an illustration, in the first phase only low altitudes might be used for settlement purposes, while in the second phase the settlements might only use high altitudes. In both cases the diversity is low. In a third case, all altitudes might be used. In this case the diversity is high. Obviously, the distance based on the vector of values has to be distinguished from the change of diversity. We use different diversity indices (Shannon-Weaver index (cf. Chap. 5), Simpson index, evenness (Oksanen, 2022; Oksanen et al., 2022) and inverse weighted rank sum) that also are indicated in the name of the indicators.

Now follows the description of the different indicators used in this study. In general, 1 and 2 indicate the two settlement patterns, while i indicates grid cells or positions in a vector. Furthermore, dens = kernel density, nn = nearest neighbour distance, cnn = cross pattern nn from one point pattern to another one, k = neighbourhood degree, v = vector of values, data = actual observed settlement pattern, random = simulated settlement pattern (Tables 4.5, 4.6, and 4.7).

Table 4.5 Displacement measures

displacement1	The kernel density estimation values for the two settlement patterns are compared by calculating $mean((abs(dens_{1i} - dens_{2i})) / max(c(dens1, dens2)))$. This is the difference in density patterns.
displacement2	The number of grid cells with a larger value in the second pattern than in the first one is divided by the number of grid cells: $\Sigma(kde_{1i} < kde_{2i})/length((kde_{1i}))$. A value of 0.5 represents an equal distribution, while lower or higher values can indicate an extension of the occupied area rather than an actual displacement.
displacement3	This displacement score is based on the nearest neighbour distances and uses the mean value of the nearest neighbours of all points from the first point pattern to the second point pattern, minus the mean of the nearest neighbour distances of both point patterns and divided by the mean of the nearest neighbour distances of both point patterns: $(me(cnn_i) - mean(c(nn_{1i}, nn_{2i})))/mean(c(nn_{1i}, nn_{2i}))$. For displacement3 only the nearest neighbour (k = 1) is used.
displacement4	This displacement score is similar to displacement3, but instead of the nearest neighbour (k = 1) the fifth neighbourhood degree (k = 5) is used. This provides a less sensitive but more robust result.

Table 4.6 Shannon-Weaver index, Simpson index, evenness and inverse weighted rank sum

even_slope	Evenness of categorised slope values
even_aspect	Evenness of categorised aspect values.
even_TPI	Evenness of categorised Topographic Position Index (TPI) values.
even_TRI	Evenness of categorised Terrain Ruggedness Index (TRI) values.
even_roughness	Evenness of categorised roughness values.
even_soil_nitro	Evenness of categorised soil nitrogen values.
even_soil_phh2o	Evenness of categorised water pH values.
even_soil_sand	Evenness of categorised sand values.
even_soil_clay	Evenness of categorised clay values.
simpson_slope	Simpson index of categorised slope values.
simpson_aspect	Simpson index of categorised aspect values.
simpson_TPI	Simpson index of categorised TPI.
simpson_TRI	Simpson index of categorised TRI.
simpson_roughness	Simpson index of categorised roughness values.
simpson_soil_nitro	Simpson index of categorised soil nitrogen values.
simpson_soil_phh2o	Simpson index of categorised water pH values.
simpson_soil_sand	Simpson index of categorised sand values.
simpson_soil_clay	Simpson index of categorised clay values.
shannon_slope	Shannon-Weaver index of categorised slope values.
shannon_aspect	Shannon-Weaver index of categorised aspect values.
shannon_TPI	Shannon-Weaver index of categorised TPI.
shannon_TRI	Shannon-Weaver index of categorised TRI.
shannon_roughness	Shannon-Weaver index of categorised roughness values.
shannon_soil_nitro	Shannon-Weaver index of categorised soil nitrogen values.
shannon_soil_phh2o	Shannon-Weaver index of categorised water pH values.
shannon_soil_sand	Shannon-Weaver index of categorised sand values.
shannon_soil_clay	Shannon-Weaver index of categorised clay values.

(continued)

Table 4.6 (continued)

rank_slope	Inverse weighted rank sum of categorised slope values: *sum(sort(*v_i*) * length(*v_i*):1) / length(*v_i*)*^{2}. The values are sorted and multiplied with their inverse rank and divided by the square number of values.
rank_aspect	Inverse weighted rank sum of categorised aspect values.
rank_TPI	Inverse weighted rank sum of categorised TPI.
rank_TRI	Inverse weighted rank sum of categorised TRI.
rank_roughness	Inverse weighted rank sum of categorised roughness values.
rank_soil_nitro	Inverse weighted rank sum of categorised soil nitrogen values.
rank_soil_phh2o	Inverse weighted rank sum of categorised water pH values.
rank_soil_sand	Inverse weighted rank sum of categorised sand values.
rank_soil_clay	Inverse weighted rank sum of categorised clay values.
hist_slope	Manhattan distance of the of categorised slope values.
hist_aspect	Manhattan distance of categorised aspect values.
hist_TPI	Manhattan distance of categorised TPI values.
hist_TRI	Manhattan distance of categorised TRI values.
hist_roughness	Manhattan distance of categorised roughness values.
hist_soil_nitro	Manhattan distance of categorised soil nitrogen values.
hist_soil_phh2o	Manhattan distance of categorised water pH values.
hist_soil_clay	Manhattan distance of categorised clay values.
hist_soil_sand	Manhattan distance of categorised sand values.

Table 4.7 Second order indices

ppa_G	G-score: *(mean(nn(*$data_i$*,* $data_i$*)) – mean(nn(*$random_{1i}$*,* $random_{1i}$*))) / mean(nn(*$random_{1i}$*,* $random_{1i}$*)).* The mean of the nearest neighbour distance of observed points to other points of the observed settlement pattern, minus the mean of the nearest neighbour distance of simulated points to other points of the simulated settlement pattern, divided by the mean of the nearest neighbour distance of simulated points to other points of the simulated settlement pattern. The G-score accounts for the internal perspective and is an inverse clustering score.
ppa_F	F-score: *mean(nn(*$data_i$*, randomi*$_j$*) – mean(nn(*$random_{1i}$*,* $random_{2i}$*)) / mean(nn(*$random_{1i}$*,* $random_{2i)}$*).* The mean of the nearest neighbour distance of observed points to points of a simulated pattern, minus the mean of the nearest neighbour distance of simulated points to other points of another simulated settlement pattern, divided by the mean of the nearest neighbour distance of simulated points to other points of another simulated settlement pattern. The F-score accounts for the external perspective and is a direct clustering score.
nSites	Relative change of the number of sites.
siteFreq	Relative change of the site frequency (sites/year).

4.4.3 Exploring the Initial Set of Indicators

The input of the synthesic analysis is a table with the transformation indicators as columns and the transformations of the different regions and period transitions as rows. Bar plots of the different rows allow for a visual comparison of the transformations. A principle component analysis of this table contributes to the question of the relationship between variables and objects. The plots of the first two dimensions are usually hard to judge because a certain degree of the variability is hidden in the remaining dimensions. The cos2 colouring (see package *factoextra*), helps to estimate which points are affected by this phenomenon and to judge whether or not it is necessary to also plot other pairs of dimensions. Keeping this problem in mind, the PCA-plots help estimate groups of similar transformations and groups of redundant transformation indices.

For a sound analysis of groups of redundant indicators, we are using a hierarchical cluster analysis (complete linkage) based on a correlation matrix (Pearson correlation index). The histogram is cut at an acceptable level (e.g. 0.05) to obtain groups of redundant indicators. One indicator might be sufficient to represent an indicator group, but the small number of transitions observed in this study prevents generalisation.

It is worth noting that the cluster analysis on the variables is required because the PCA focuses on re-projecting the data to another set of dimensions. In this study we are not interested in obtaining artificially transformed variables with reduced dimensions, but in deciding on a reduced set of original indicators.

4.4.4 Change Profiles

When looking at change, one inevitably has to deal with three components: time, the before, and the after. Even though it has been known since the introduction of Albert Einstein's (1905) theory of relativity that the Newtonian concept of an absolute time, which passes equally at every place in the universe, is wrong, time still plays a key role in measuring change. Without the measure of time, no change can be detected because the reference point is missing.

Change can be quantified by comparing specific aspects of two time slices. Relative time series, as they result from relative chronology, also lend themselves to such a consideration, since the sequence of events can be determined. In a change profile, time is plotted on the x-axis and individual changing processes are quantified on the y-axis. A variation at a certain point in time, relative to the previous time period, is entered with a normalised value. If there are no further changes in the following period, the value to be entered is zero in a systemic perspective.

If, for example, several new crops are developed synchronously with each other, there will be an increase in the corresponding value. Assuming this condition persists for a few generations, the value drops to the baseline. Once a crop plant establishes itself, another rise appears. This is because the abandonment of previous practices also represents a fundamental change and is not synonymous with a "step backwards" or a "return to the previous state". Phases with a high rate of innovation result in a high rate of change, as does the manifestation of a new standard. Before a transformational phase, the values might differ slightly throughout the parameters. During the transformational phase, there is a clear increase in the change profiles, either staggered or synchronous. After the transformative process, the change values "calm down" again, which can be recognised by low values within the different parameters of the change profile. For the graphical representation of change profiles, the value of a factor is plotted as a bar plot. If the rate of change remains constant, and more or less the same number of individual aspects change, the height of the individual bars remains similar. The value is created by the difference of the quantified change to the previous time span: change = $abs(n_{after} - n_{before})$.

In order to display factors synchronously, the individual change values are lined up one above the other, aligned according to absolute chronology and grouped according to parameters. The independence of the factors is not guaranteed (see discussion on the latent influence of climate), so they are correctly presented as individual bars. The values of change are plotted on the y-axis and normalised beforehand to avoid over-estimating factors with good data or high counting rates. The absolute numbers do not imply any valuation of the importance of the factor, but result from the nature of the data. The significance of a changing factor does not necessarily depend on the count rates, but on the change within the behaviour that resulted in this particular change. The deposition of hoard finds, for example, ends in Central Europe with the beginning of the Early Iron Age. This factor of the ritual domain, which reflects fundamental changes in the concept of the afterlife, can be represented by presence/absence. The number of certain artefacts in graves, on the other hand, is better represented by quantities. By normalising the rates of change, the influence of count rates and quantity of artefacts is minimised and presented in a comparable way. The quantification of the rate of change is strongly determined by the respective factor.

Change profiles in the present case studies show the absolute chronology[2] on the x axis. Since relative chronologies are accompanied by the assumption of epoch transitions and often also transformations, absolute dating is to be preferred. Furthermore, two difficulties occur when using a relative time scale. First, the definition of chronological stages is determined by the archaeological material. Naturally, it is easier to define epoch boundaries when the material culture changes fundamentally. However, relative time scales are not evenly distributed, so that a phase can cover a significantly different length of time. Hence, for the creation of a change profile, the relative chronology should be mapped onto an absolute chronology. A fuzzy approach can be used to mitigate the dominance of the relative stage allocations, for example by distributing the numbers over the absolute time. If, for

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[2] This differs from the graphical representation for the identification of indicators (see Fig. 4.4). Here, the explicit transitions are used to display changes between the two assumed phases.

example, the number of settlements is plotted as a factor, insufficiently precisely dated sites can be divided among the time classes with a fuzzy approach and thus relative phases that are easier to identify can be balanced out. Second, the use of absolute chronologies allows to easily in-cooperate precisely dated material. Using a fuzzy approach allow here again to take in to account method inherit dating imprecisions.

4.4.5 Software

The analyses in this chapter were conducted using R (R Core Team, 2022) and the R packages geodata (Hijmans et al., 2023), terra (Hijmans, 2023), sf (Pebesma, 2018), spatstat.geom and spatstat.explore (Baddeley et al., 2015), FactoMineR (Lê et al., 2008), factoextra (Kassambara & Mundt, 2020), and ape (Paradis & Schliep, 2019).

4.5 Results

4.5.1 Transformation Spectra

For presenting the results, all transformation indicators are compiled in one table with indicators in columns and transformations in rows (Fig. 4.3). The indicators form a kind of transformation profile that can be visualised with bar plots for each transformation. For these bar plots we omit the y-scale since the information of the normalised indicators also can be understood without looking at the actual numbers.

The transformation indicators help to characterise the transformations in detail. We start with the two transformations in Baden-Württemberg, which were recorded from the perspective of the graves and the settlements respectively. For the sake of simplicity, we call the transition from Ha C to Ha D the first transformation and that from Ha D to Lt A/B the second. First, we turn to the topographic indicators. Slope changes strongly in the first transformation and less in the second, with diversity increasing strongly at first and increasing little, or decreasing slightly, in the second transformation. Aspect also changes strongly in the first transformation and less in the second. The diversity of the values, however, is hardly changed in the first transformation and increases slightly in the second. The same pattern of first strong and then weaker change is also observed for the TPI, whereby the change is smaller for the settlements than for the graves. Diversity increases at first and then remains the same or even decreases slightly. The differences in TRI and roughness decrease from the first to the second transformation for the graves and remain more or less the same for the settlements. Diversity first increases and then tends to decrease.

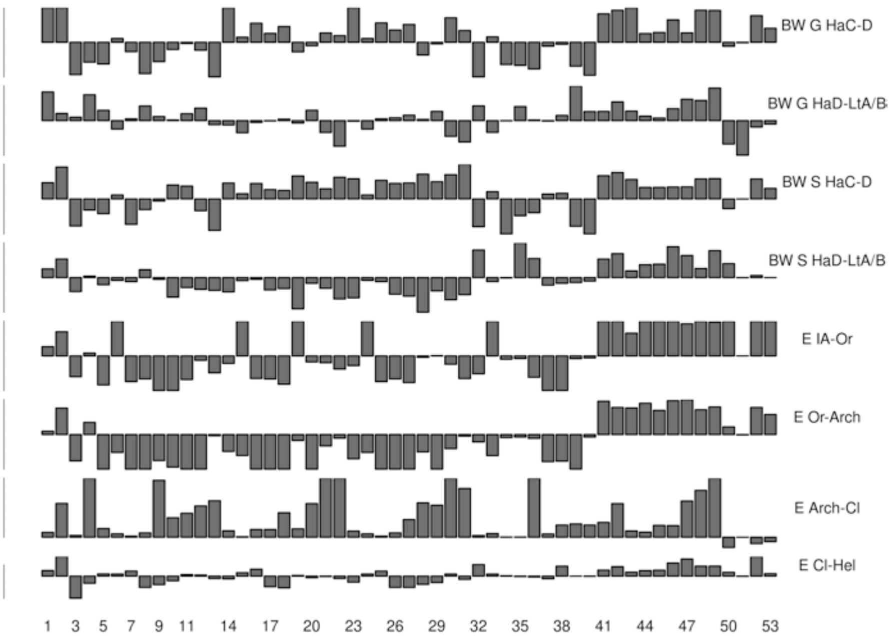

Fig. 4.3 Bar plot of the initial location-based transformation indicators for all considered Iron Age transformations

The chemical soil indicators show a heterogeneous picture of distances. Diversity decreases for the graves in the first transformation and in the second, while this is reversed for the settlements. It should be borne in mind that these indicators certainly do not provide primary evidence, as soil chemistry may have changed more than the other parameters. As indirect indicators, however, they may well show changes. In any case, their interpretation is difficult. The changes in soil types are easier to assess here. The changes in clay decrease from the first to the second transformation, while diversity increases strongly in the first transformation and then slightly in the second. For the sand, we can observe that the distances tend to increase from the first to the second transformation, with diversity first increasing slightly. For the graves, sand decreases in the second transformation, but increases for the settlements. Overall, the increase is stronger for the settlements.

The first displacement score is slightly positive, especially for the graves, indicating a slight shift in settlement space. High values of the second displacement score for the first transformation indicate an increase in the settlement area, while low values for the second transformation show a reduction. The negative values of the third displacement score in the first transformation indicate a slight shift and densification of the settlement areas. This effect is significantly lower in the second transformation. Both are confirmed by the fourth displacement score with somewhat more moderate values.

We turn now to the second order effects, for which we only have two indicators: the G-score and the F-score. The scores we are using can be interpreted as a kind of inverse (G) or direct (F) clustering coefficient since it measures the neighbourhood distances in relation to a certain base line. The G-score decreases slightly in both transformations and only increases slightly for the settlements in the second transformation. The F-score, on the other hand, first increases and then decreases, with the graves being more subject to this change. Overall, the clustering reaches its maximum in Ha D, with the internal structure of the clusters remaining largely the same. The G-score shows obviously smaller effects than the F-function. This suggests that it is mainly the large-scale structures that change, while the local or cluster-internal structures, i.e. the view from within, vary less. The difference in chronological phases indicates an increase in clustering in the external (F) view at the transition from Ha C to Ha D. This may be because settlements are becoming more ephemeral (more settlement sites in the same time and in close proximity) or because isolated settlements are disappearing. The pattern is consistent with the concentration of power discussed by Biel (1987), Sievers (1982) and Pare (1992), but can also be explained by a change in land use or an increase in insecurity. At the transition from Ha D to Early Latène a decrease of the clustering can be observed. The numbers of sites show a clear change and the site frequencies do not differ much because the phases have similar length. In the first transformation, the numbers of graves, in particular, increased significantly. In the second transformation, the numbers of graves decrease while the numbers of settlements continue to increase slightly.

Overall, the picture of a Ha C to Ha D transformation emerges, which is clearly more substantial than, but also somewhat different to, the transformation from Ha D to Lt A/B.

Let us now turn to Etruria. Here we have data on four transformations, but only on one type of site at a time, the settlements. The first two transformations show considerable changes while the later two are characterised by rather low change values. For the first two transformations, the diversity of the slope increases while it decreases slightly with the other transformations.

The same is also true for the aspect; the first two transformations have high change values while the later two transformations show lower change values. The diversity of the aspect shows rather low values throughout. The change values and the diversity of the TPI show the same patterns as for slope. TRI and roughness also have higher values in the first two transformations than in the later two transformations. The diversity of TRI and roughness decreases in the first, second and fourth transformations, and only increases in the third transformation. The change in chemical soil values is quite strong in the first two transformations, moderate to strong in the fourth transformation and rather small in the third transformation. The diversity of the chemical soil values increases according to the already known pattern in the first two transformations, drops somewhat during the third transformation and shows only slight changes in the fourth.

Sand and clay change strongly in the first and third transformations, slightly less in the second and even less in the fourth. The diversity of sand increases slightly in the first transformation, more strongly in the second, drops noticeably in the third transformation and is only slightly influenced by the last transformation. For the clay, an increase can be seen in the first transformation and a decrease in the third transformation. The other two transformations show low change values.

The first displacement score shows rather low values in all transformations, while the second shows predominantly medium values and thus small changes. Only for the fourth transformation is the value somewhat higher and indicates an expansion of the settlement area. Displacement score 3 shows negative values in the first, second and fourth transformations, indicating densification, which only decreases in the third transformation. Displacement score 4 has a negative value only in the fourth transformation and increasingly positive values until then. Thus, while the nearest neighbour moves closer in the first two transformations, the fifth neighbour moves further away in the first three transformations.

This picture is also confirmed by the G-score and F-score. The inner clustering decreases in the first two transformations and then remains the same. Viewed from the outside, the clustering also decreases in the first two transformations, then increases and then decreases again in the fourth transformation. The number of sites increases in the first two transformations, then decreases, and increases again in the third transformation. The first transformation has a strong growth of the site numbers that is even stronger when looking at the site frequencies, as well as an internal and an external de-clustering. In combination with the slight expansion of the settlement area this speaks to a stronger and more systematic spatial organisation. This continues with the second transformation that, in contrast, maintains the internal settlement structure. The third transformation with decreasing site numbers, increasing clustering from the external perspective, and the preservation of the internal structure, seems to reverse the process. This transformation is consistent with a certain centralisation process that abandons isolated areas and focuses on the urban sites. Finally, the fourth transformation resembles the second one, but the increase in site numbers becomes less pronounced when looking at the site frequencies.

Overall, a dichotomy emerges with strong changes in the first two transformations. The later two transformations are less pronounced and partly opposite. The third transformation, in particular, seems to differ from the others and to represent a kind of consolidation.

Though this description of the transformations does not address all aspects available with the transformation indices, a rather rich technical image of the transformations in the different regions emerges. The simple transformation indicators paint a picture of a rather complex settlement development that involves a multitude of decisions. At the same time, the indicators also allow a comparison of regions that offer entirely different source situations. This is made possible by the fact that the indicators are quite abstract and have been partly adjusted by multiple normalisation. The price to be paid for this advantage is that it is more difficult to assess the concrete characteristics of the respective transformation processes. This cannot be done at the level of abstraction necessary for comparison and must be done in the individual regions against the background of the individual developments and parameter characteristics. Since this is not the aim of this chapter, we will not try to reduce the abstraction, but rather to increase it. This is done with the following analyses and visual representations.

4.5.2 Transformation Plot

The transformation plot presents values of all transformation indices at the date of the transformation. In order to better see the values on the x-axis, the square-root of the indices is used. This means that low values (much smaller than 1) are scaled up and that values larger than 1 are scaled down. The mean value of all indicators per transformation is presented as solid black point. In addition to this effect, all indicators become positive and hence, measure the degree of transformation independent of the decrease or increase of the value.

The transformation plot (Fig. 4.4) shows that the mean values of the early transformations (before 500 BC) all have slightly higher mean values than the later ones. This change in the transformation degree is independent of the region, since it affects Baden-Württemberg as well as Etruria. The black horizontal line aims to highlight this effect. This might indicate supra-transformation at the next level of abstraction. Judging the significance of this effect cannot be based on statistical significance tests only, but requires a deeper understanding of the relationship between the indicators. For now, we just can take this assumed supra-transformation as a hypothesis for future research.

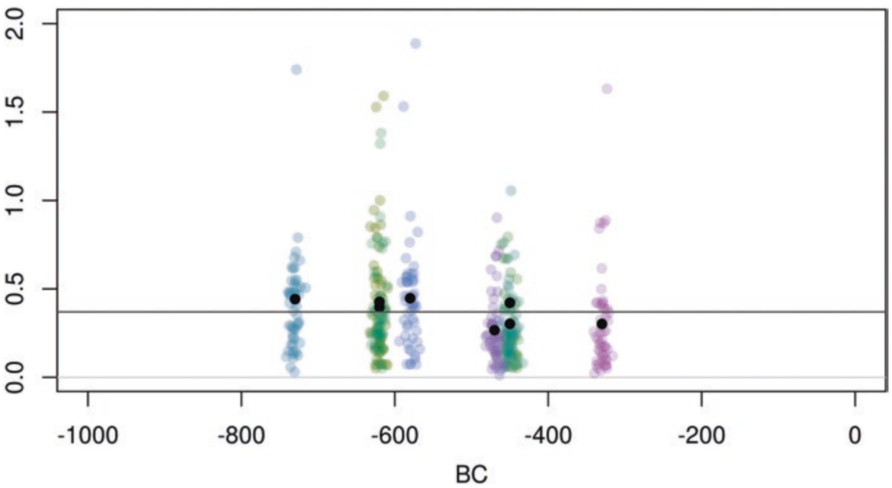

Fig. 4.4 Transformation plot of all considered Iron Age transformations. The colours identify index values from the same transformation in a specific region and the black dots are the mean values of each transformation. The horizontal line is merely for orientation; to better distinguish the mean values of the early and late transformations

4.5.3 Synopsis of Preliminary Location Parameter

The synopsis is dedicated to the question of how the transformation indicators are related. A principal component analysis can help with exploring the data-inherent structures and hence shed light on the relationship of variables as well as of objects.

The scree plot (Fig. 4.5) reveals that 67% of the variance in the data is covered by the first two dimensions. Though a considerable part is hidden in the remaining dimensions, this value suggests that most information is visible in a plot of the first two dimensions. The $\cos^2$ value shows how much an original indicator contributes to the first two new dimensions. The plot indicates that some indicators are highly correlated and hence, redundant.

The variable and object plots (Figs. 4.6 and 4.7) of the transformations show that the transformations are different, but that some form a kind of cluster. In particular, the clusters of the early and late transformations in Baden-Württemberg, which indicate a similarity of the transformations perceived from the settlements and from the graves, assures us that the indicator approach makes sense.

For the actual detection of the groups of indicators, we use a cluster analysis of the original data because a reduction of the dimensions cannot be covered by theory. Instead of a distance matrix, we use a correlation matrix, since we aim to find clusters of highly correlated indicators. A heatmap (Fig. 4.8) shows this correlation matrix.

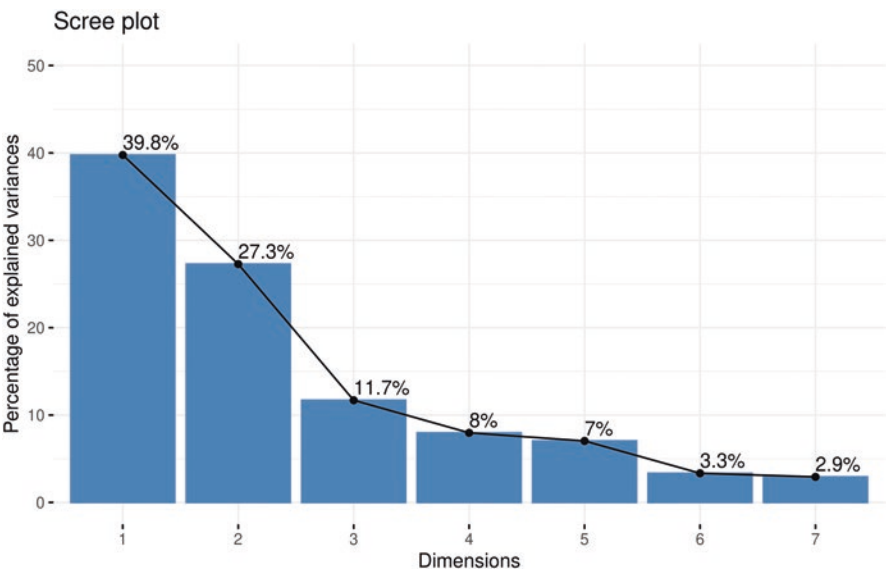

Fig. 4.5 Scree plot of the principle component analysis of the initial transformation indicators

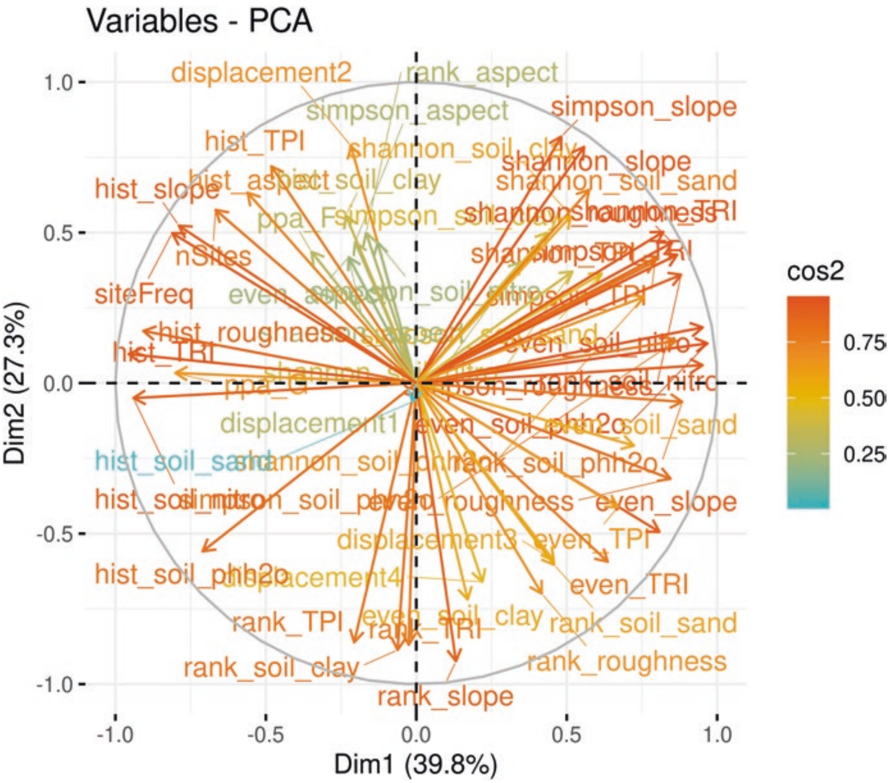

Fig. 4.6 Variable (indicator) plot of the principle component analysis of the initial transformation indicators

A hierarchical complete linkage cluster analysis produces a dendrogram that can be cut at a level of 0.05 to reveal the clusters of highly correlated indicators. Each indicator is assigned to a cluster and for each cluster a representative can be selected.

4.5.4 Indicator Selection

It emerged that most indicators provide specific aspects for the characterisation of sites. Nonetheless, only part of the information is useful for an identification. We hence develop two sets of indicators, one for identification and one for characterisation. The latter includes more correlated indicators than the first one. Each displacement score provides information complementing each other. Because the distances are also covered by the G-scores and F-scores, we keep displacement 1 and 2 for identification and use all indicators for characterisation.

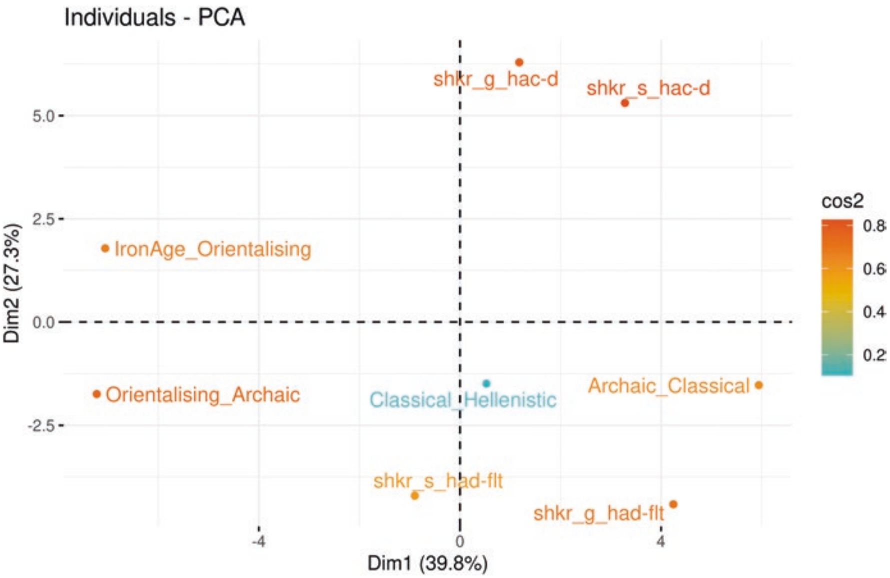

Fig. 4.7 Object (transformation) plot of the principle component analysis of the initial transformation indicators

The analysis reveals that the different diversity scores are highly correlated. The evenness seems to be the most powerful diversity indicator, or rather inverse diversity indicator, in particular because it makes the Shannon-Weaver index comparable. This leads to the decision to keep evenness for the identification indicator set and evenness and ranking for the characterisation data set.

Additionally, as expected, TRI and roughness are highly correlated, so that we keep TRI for both sets. The chemical soil data are hard to judge for our purpose, so that they are not included in our indicator sets.

All histogram-based distance scores, as well as the second order scores and the site frequency, are kept for both indicator sets. The site number offers additional information involving the length of the phases compared to the site frequency, but is much less telling than the site frequency and, hence, is excluded.

4.5.5 Change Profiles for Early Iron Age in Baden-Württemberg (Fig. 4.9)

The case study on Southwest Germany serves as an example to show how additional information is involved. The change profiles visualise parameters from different domains and climate change.

Climate change reaches a maximum in the seventh century BCE and a phase of change starting in the third century BCE. In the period between, climate change is

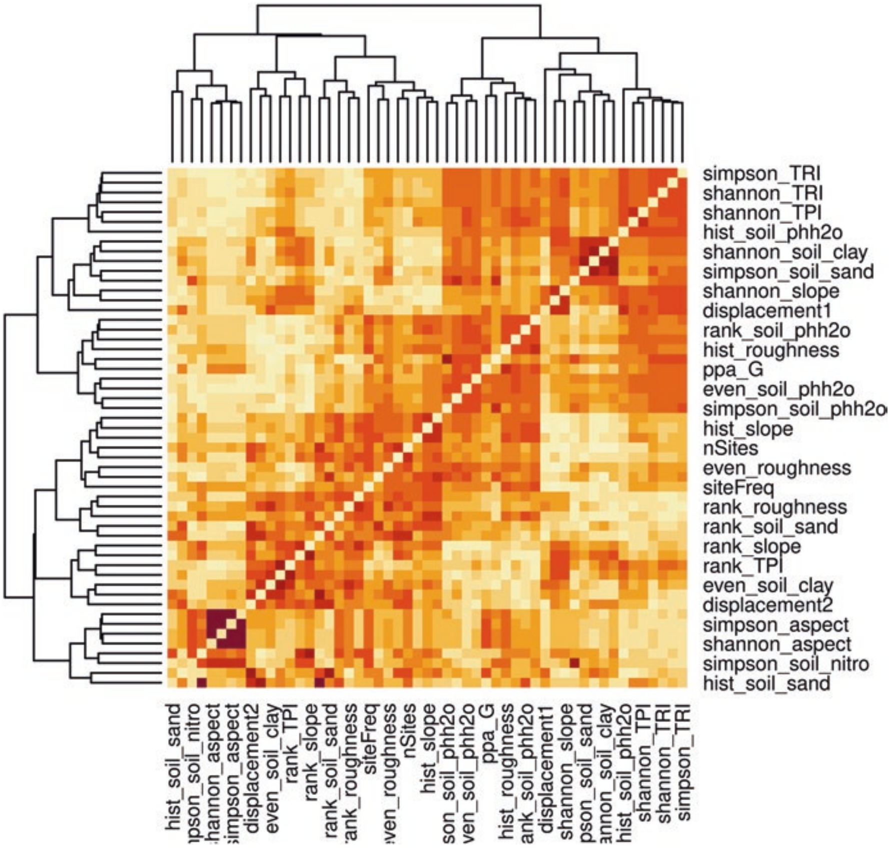

Fig. 4.8 Heatmap of the Pearson correlation of the initial transformation indicators

less pronounced, with a local maximum in the mid-fifth century BCE. This local maximum coincides with maximal change values in most domains. For the settlement and grave numbers, that value is even higher than the change of the previous transformations. However, caution is required with these numbers. The change values map the hierarchy of the chronological system, and the strong change in question corresponds with the Hallstatt and Latène transition. Though this effect is real, to some extent the aoristic dating reinforces the main transitions. The comparison with the transformation plot (see Fig. 4.4), which is less prone to have this aoristic bias because all observations are relative to a specific baseline, shows that the trend is the same: stronger change in the Hallstatt period, including the Latène transition. If we consider the bias, the indicators map the well-known transformations in a convincing way. It is just the correlation with climate change that is rather poor, but a convincing correlation cannot be assumed on a regional level.

The other domains suffer far less from the aoristic bias of the change values, because the poorly dated sites play a much smaller role in this subset of the data.

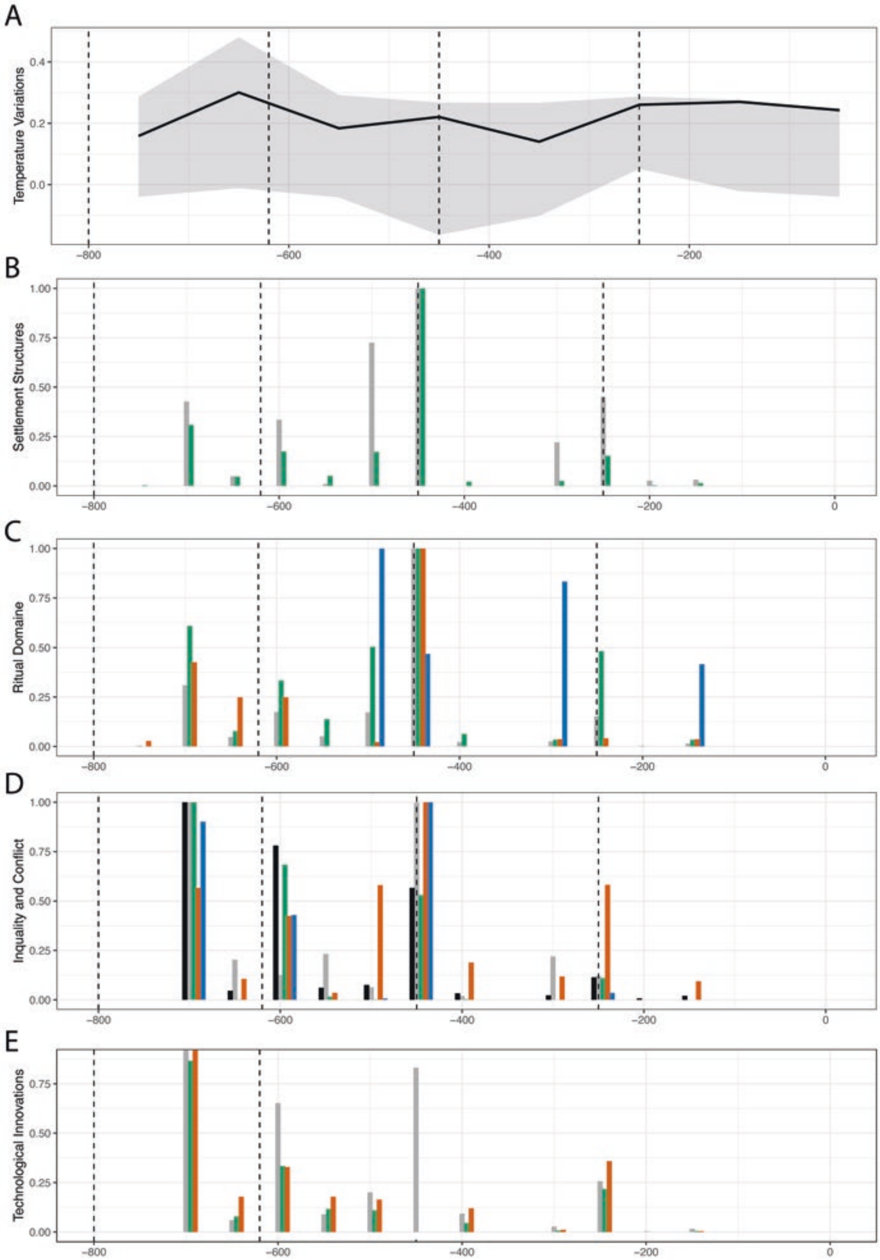

Fig. 4.9 Change profile for the Early Iron Age in Baden-Württemberg (**A**) Temperature variation; (**B**) Change in settlement structures (grey: number of settlements; green: graves); (**C**) Changes in ritual domain (grey: graves; green: inhumation; orange: cremation; blue: hoards); (**D**) Changes in inequality and conflicts (grey: gold objects; green: gagate objects; orange: swords; blue: daggers; black: lance / arrows); (**E**) Technological innovations (grey: iron objects; green: bronze objects; orange: Fibulae); dashed lines indicate the main chronological phases

These other domains, in particular, provide additional information for comparing the different transformations. The ritual domain has a dominant change in burial practices in earlier phases, while the change in hoard numbers becomes relevant from the late fifth century BCE onwards. This is particularly interesting because it does not coincide with the main chronological transition.

The social sphere, involving inequality and conflict, provides a particularly detailed pattern. With a very strong transformation at about 700 BCE, we enter a phase of social visibility that is usually considered to be the emergences of elites and prestige. The next strong transformation at 600 BCE amplifies this process. This phase ends with the main chronological transition in the middle of the fifth century BCE. It is worth mentioning that only the sword numbers change frequently throughout the younger transformations. This might be caused by a change from prestige to status, and the role of the sword as a status indicator with changing relevance.

The technological domain shows a similar pattern. At about 700 BCE, maximal values are reached in nearly all indicators from this domain.

The overall pattern is that of a main transformation at the main chronological transition in the mid-fifth century BCE, with more pronounced sub-transformations in the early part of the period. Comparing the different domains, two patterns can be distinguished. The first pattern, represented by the settlement and ritual domains, shows a noticeable change at 700 BCE and an even stronger one at 500 BCE. The second pattern, represented by the social and technical domains, shows a strong transformation at 700 BCE, a decent one at 600 BCE and a rather minor one at 500 BCE. These patterns indicate that social processes and technical innovations trigger the process characterised as the "emergence of elites", while settlement structures and ritual aspects are mainly involved in a later transformation of the society. A first process focused on the formation of a specific social group, which supports and accelerates technical developments, is followed by a second process that involved the whole society and includes a kind of social consolidation. The less-pronounced transformations in the social and technological domains prepare the way for the second transformation process.

This analysis indicates that different processes took place, which affected the domains differently. Nonetheless, the different transformations are likely to have influenced each other and to be part of one longer transformation process that is not uniform, but has distinct and characteristic phases. Even domains with low change values play an integral role in this process.

4.6 Discussion

The main idea of this chapter is to make transformations comparable by introducing an abstraction layer, with transformation indicators that indicate the degree of change between two phases. This approach can be applied to completely different sets of archaeological data as long as the geographical location and the chronology of the sites are available.

An important question is, which set of indicators is sufficient for characterising the transformations and hence for measuring the degree of change? We were able to reveal that some indicators are correlated.

The clusters can contain two types of indicators: indicators that are actually redundant and indicators that only correlate in the considered transformations (see Table 4.8). Since only a few transformations were considered in this chapter, the second category should be taken into account and indicators should not be excluded prematurely. We therefore only exclude indicators that are both strongly correlated and seem to be related in terms of content. Thus, at least one indicator is obtained from each cluster.

Since many indicators cover very similar things, for example the different displacement scores, it could be assumed that many indicators are redundant. In fact, however, only a few indicators seem to be redundant.

The numerous indicators, many of which are interrelated in terms of content, have an astonishingly low level of redundancy. This gives us a large number of relatively simple indicators that all describe certain aspects of the transformations and can characterise them well and in a differentiated way.

This observation opens the door for developing a transformation classification based on the transformation indicators. Different kinds of transformations can be identified and characterised, and perhaps even supra-transformations can be detected.

The transformation indicators used in our case study show a different dynamic. Some categories show small changes, while others show rather substantial changes. We assume the reason to be partially different degrees of dynamics within the different categories. Though this is probably mapping real behaviour of the different categories, this phenomenon makes a comparison rather difficult because the overall result is dominated by the dynamic categories, no matter how relevant they are. A solution to this problem could be a calibration of the change indicators according to the categories. The result would be transformation indicators that show the same level of change in general. It will not be possible to calibrate the values using "real" values. However, a calibration using some standard case studies might be sufficient for the purpose of gaining better comparability. The development of this kind of

Table 4.8 Indicators for identification or characterisation of transformations

Transformation indicators for identification:	Transformation indicators for characterisation:
displacement1, displacement2, even_slope, even_aspect, even_TPI, even_TRI, even_soil_sand, even_soil_clay, hist_slope, hist_aspect, hist_TPI, hist_TRI, hist_sand, hist_clay, ppa_G, ppa_F, siteFreq	displacement1, displacement2, displacement3, displacement4, even_slope, even_aspect, even_TPI, even_TRI, even_soil_sand, even_soil_clay, rank_slope, rank_aspect, rank_TPI, rank_TRI, rank_soil_sand, rank_soil_clay, hist_slope, hist_aspect, hist_TPI, hist_TRI, hist_sand, hist_clay, ppa_G, ppa_F, siteFreq

calibration certainly has to consider the kind of transformation typology mentioned above.

It should be mentioned, that the set of transformation indicators considered in this chapter is rather limited. In particular some scientific data, such as stable isotopes (e. g. Ventresca Miller et al., 2021) or aDNA data (e. g. Gretzinger & Schiffels, 2020; Schiffels et al., 2016; Schmid & Schiffels, 2023) could prove to be extremely helpful if they become available across the board.

4.7 Conclusion

Summing up the results of the transformations in South-West Germany, and including the additional information besides the simple settlement pattern indicators, we can characterise the transformations. When we consider the first transformation, the transition from Ha C1 to Ha C2 is of high intensity. Changes mainly concern gold objects, gagate, weapons – with the exception of swords, which have half the change intensity – and fibulae, as well as iron and bronze items. Less intense, but still substantial, are the components of the settlement patterns and the burial rituals. The swords are at the same level. Hoards do not play a role in the change. Overall, the focus of this transformation is obviously on the social and economic domain. Though not one of the transitions traditionally considered highly relevant, this transformation shows strong activities in the technological and social sphere, where a reconfiguration of society that concerns all of its parts is underway.

The next transformation, the transition from Ha C to Ha D, is rather of medium intensity. Only the displacement of the sites is strong. Gagate, iron, and lances are at a medium level, while settlement patterns, burial rituals, gold, swords, daggers, bronze, and fibula are factors of low intensity. The type of settlement pattern remains, while the settlement locations change. Besides this observation, this transformation is mainly concerned with the social and technological domains. This transition is traditionally perceived as the emergence of elites. It somehow continues the trend of the previous transformation. The rather large lance change value indicates that it still does not only concerned the elites.

The third transformation is the transition from Ha D1 to Ha D2, and this one is even less intense than the previous one. The strongest factor (gold) with low change intensities is from the social domain. Inhumation graves, settlement patterns, lances, and the technical domain play an even smaller role, while the remaining factors do not contribute to the transformation at all. If we want to name a focus of this transformation, that would be the social domain. The rather short Ha D2 phase is introduced by a transformation that, though not very intense, mainly concerns the elites.

The transition from Ha D2 to Ha D3 is stronger, and the most intense factor is hoards, with a very strong change. The settlement patterns also show a strong change, followed by the swords and the inhumations. Lances, gold, and technological factors play a minor role in small change intensities. The focus of this transformation is on settlement patterns and the ritual domain and hence, it represents a new type of transformation compared with the previous Iron Age transformations. With Ha D3, we are entering a kind of culmination of the social processes of the Hallstatt period, and at the same time a certain consolidation.

The transition from the Hallstatt to the Latène period is also a rather strong transformation that concerns all domains. Hoards, gagate, and lances show medium change intensities and represent the smallest factors of change in this transformation. The settlement pattern is at about the same level. Here, we can perceive a strong change in settlement numbers and moderate changes in the site locations and the type of settlement patterns. It is hardly possible to define a focus for this transformation. The Latène period is not only marked by a new art style, but also by a very strong ritual component. At the same time, a social transformation that affects all parts of society takes place, with the elites particularly affected as they become less visible.

Our final transformation is the transition from Latène B to C, which shows rather low intensities. The strongest factors are the swords, the inhumations and the settlement patterns on a medium level, while all other factors show minor or zero contribution to the transformation. The settlement patterns and the ritual domain seem to dominate the focus slightly. While the later part of the Early Latène period (Lt B) is, in particular, considered a kind of democratisation, the transition to Lt C is marked by the swords and conflict-oriented factors in contrast to the prestige of social status.

The case studies in this chapter suggest that a set of location-based transformation indicators can be used to indicate, characterise, and measure the degree of transformations. The change profiles appear to be a useful tool for comparing and integrating the multitude of location-based transformation indicators and information from other domains. This allows for the development and communication of rather complicated or even complex transformation interpretations.

The correlation between similar transformation indices is much smaller than expected and hence, they offer a better and more detailed characterisation of the transformations. The change profiles allow the easy integration of additional information. This allows a deeper understanding of the individual transformations and even of interrelated transformations. For the case study from South-West Germany, we revealed two interrelated transformation processes. The first process focuses on the formation of the elites, which supports and accelerates technical developments. This prepared the way for the second process, which affects the whole society and involves a kind of social consolidation.

A remaining problem is that different domains and sub-domains, represented by indicator types and single indicators, have different natural degrees of change or different natural variability. Though this is a result in its own right, it makes comparison more difficult. A calibration of the change factors, according to several very different case studies, could be a solution and would at the same time be a sound measure of the natural variability. This suggestion goes beyond the present chapter, however, due to the required number of case studies.

The change profiles suffer from an aoristic dating bias that has to be considered with the interpretation. Because of the simple methods and greatly limited data requirements, the location-based indicators appear to be a rather simple though powerful tool, but obviously they cannot cover all domains. A next step could be to develop similar sets of indicators for other domains.

With the diachronic representation of the changing processes via synchronous quantification, change profiles make it possible to integrate information from different domains for the interpretation of transformations. The benefits of the method provided here are twofold: first, by using a widely available set of parameters (in this case of the location of sites) change profiles can identify indicators for well-known transformations. This needs to be transferred to other assumed indicators and applications. Second, change profiles provide a tool for visualising heterogeneous data and deepening our understanding of intertwined parameters.

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