Fables of the past: landscape (re-)constructions and the bias in the data

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ABSTRACT – *Prehistoric landscape reconstructions are still considered an unsolved methodological issue in archaeological research, and this includes the perception and transformation of an individual landscape in relation to situational and local ecosystem performances. Which parts of the landscape offered the potential for land-use and which areas were rather unsuitable due to a variety of environmental preconditions? The modern perception of the archaeological record that is distributed in the modern landscape does not necessarily represent a realistic dispersal of past human activity, but rather reflects the current state of archaeological research and modern land-use strategies. This contribution provides a critical assessment of spatial analyses of large and unstructured archaeological datasets and the non-reconstructibility of past, individually perceived palaeolandscapes.*

KEY WORDS – *spatial analyses; GIS; multivariate modelling; landscape archaeology; human ecology*

Bajke o preteklosti: krajinske (re)konstrukcije in pristranskost podatkov

IZVLEČEK – *Rekonstrukcije prazgodovinske krajine še vedno veljajo za nerešeno metodološko vprašanje v arheoloških raziskavah, kar vključuje zaznavanje in preoblikovanje posamezne krajine glede na situacijske in lokalne učinke ekosistemov. Kateri deli pokrajine nudijo potencial za izrabo zemljišč in kateri predeli so zaradi različnih okoljskih danosti manj primerni? Sodobno dojemanje arheoloških zapisov, ki so razširjeni v sodobni krajini, ne predstavlja nujno realne razpršenosti človeških aktivnosti v preteklosti, temveč odraža trenutno stanje arheoloških raziskav in sodobne strategije rabe krajine. V prispevku nudimo kritičen razmislek o prostorskih analizah velikih in nestrukturiranih arheoloških podatkovnih baz in neobnovljivosti preteklih, posamično zaznanih paleokrajin.*

KLJUČNE BESEDE – *prostorske analize; GIS; multivariatno modeliranje; prostorska arheologija; človeška ekologija*

Introduction

Remote sensing techniques and Geographic Information Systems (GIS) have proven to be useful tools in environmental research, and particularly in modelling supraregional surface developments and land-cover changes (*Kaplan, Avdan 2017; Landuyt* et al. *2019; Malekmohammadi, Jahanishakib 2017; Shen* et al. *2019*). Open source medium-resolution satellite images from the Landsat and Sentinel missions are used to monitor and map surface cover modifications through multispectral analysis (*Stratoulias* et al. *2018*). These methods are extended by active sensor radar analysis that allow for surface observa-

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tions during cloud-cover or without sunlight (SAR – Synthetic Aperture Radar) (*Cao* et al. *2019; Dabrowska-Zielinska* et al. *2016; Landuyt* et al. *2019; Mleczko, Mróz 2018*). The massive anthropogenic pressure on today's ecosystems drastically expands the need for large-scale surface monitoring. This is particularly visible in the growing social and cultural vulnerability to extreme weather events, which requires the intensification of large-scale surface monitoring to understand the relationship between natural ecosystem impacts and cultural heritage management. The integration of landscape connectivity, the human as vulnerable agent, and increasing ecosystem susceptibility plays a key role in landscape archaeological research (*Kempf 2019b; Lasaponara, Masini 2006; 2011; 2013; Masini, Soldovieri 2017; Morrison 2013*). The evaluation of the distribution of archaeological sites and human behaviour in a specific landscape demands deeper knowledge of the geographical interconnectivity of the environmental preconditions. Intense land-use and settlement activity in particular severely modified the earth's surface in past centuries, building a variety of *cultural landscapes* on top of each other. It is a methodological challenge to evaluate the patterns and structures behind the distribution of archaeological sites in the landscape, in order to rapidly draw conclusions about landscape permeability, cultural exploitation, and the human-environment interaction of premodern societies. This contribution aims to highlight the interface between the monitoring of surface dynamics, the reconstruction potential of palaeoenvironments, and the analysis of spatial patterns of archaeological site distribution. The following questions are of central importance in this context:

❶ How is our modern understanding and perception of an archaeological landscape biased by modern land-use concepts, settlement activities, and recent structural surface changes?
❷ How can GIS-based environmental models, remote sensing applications, and statistical analysis explain spatial patterns of archaeological site distribution?
❸ How can these concepts contribute to a comprehensive landcover reconstruction?

Fables of the reconstruction? Landscapes, ecosystems and affordances

Landscape archaeology is in vogue, and there are increasing discussions about the terminology of landscape. This has led to a mixture of concepts and definitions from many scientific fields and subcategories, resulting in an increasingly blurred terminology that makes it difficult to understand the methodology and its limitations (*David, Thomas 2010; Meier 2017*). Landscape archaeology has a rather short history, and only came into use in the mid-1970s (*David, Thomas 2010; Fleming 2006*). Moreover, it took until the 1980s and Colin Renfrew's advance in the field of cognitive archaeology for landscape archaeology to become established in post-processual approaches (*Doneus 2013*): the categorical separation or inclusion of culture and environment (*Ingold 2000; Meier 2009*). Basically, landscape archaeology has now become an umbrella term for spatial patterns in archaeology (*Doneus 2013*). It aims to understand how space has been organized and structured in premodern societies through the emotional meaning, experience and categorization of landscapes (*Meier 2009*). Landscape archaeology thus does not simply represent an extension of environmental or settlement archaeology, but in contrast, a conglomerate with explicitly cultural-scientific methods for the social reconstruction of spatial life worlds (*Meier 2017*). The integration of trans-regional geographic networks and the dissolution of the local environment enable an objective consideration of resource distribution, land-use, supraregional communication, mobility and exchange, as well as transcultural adaptation and development processes.

Human ecology and the spatial-temporal scale of landscapes affordances

Beside a conceptual framework of archaeological criteria to define spatial patterns of human behaviour, landscapes are considered as being composed of many characteristics. Michel Baguette *et al.* (*2013*) consider the landscape as the most appropriate spatial scale to define ecological networks in ecosystems. According to the authors, the extreme difference in the perception of the term landscape emerges from the divergence of the concepts of biogeography and behavioural ecology. Biogeography defines the landscape as a clearly categorized spatial organization with a homogeneous geomorphology and climate. Behavioural ecology, on the other hand, defines the landscape as the individual's perception of the environment and the spatial extent of his/her activity range as a function of the lifetime spread of the organism (*Baguette* et al. *2013; Gurrutxaga* et al. *2010; Kupfer 2012; Schaich* et al. *2010*). It is obvious that landscapes can hardly be defined solely through spatial determination of human-environment interactions without adding a temporal component and an individual dimension of landscape perception.

The temporal component is a methodological confusion in landscape archaeology. This is particularly important in terms of the differentiation of event and process. Events seem to take place on a short-term scale with noticeable and mostly severe impacts on ecological habitats and sociocultural human systems (*Berglund 2003; Büntgen* et al. *2011; Toohey* et al. *2016*). However, the differentiation between event and process in archaeology is more determined by the material consequences than the environmental triggers. As a result, short-term events tend to blur in long-term chronological categorization. They are not detectable until their consequences are not manifested materially, socially and culturally. Events, processes, and the spatial parameters of landscape patterns and susceptibilities are inevitably linked, and form the specific dynamic character of landscape ecology and archaeology.

Tracing where and when groups and individuals have settled and reshaped a particular place for a certain reason is of central importance in archaeological research, and especially in cultural heritage management (*van Leusen, Kamermans 2011; Verhagen* et al. *2010; Verhagen 2018*). The basis for this is relatively simple: human behaviour is patterned (*Brandt* et al. *1992*). The resulting structures follow the conceptual landscape fragmentation of premodern societies, and eventually their interaction with their environment (*Verhagen 2007*). This geographic fragmentation and the patterned human behaviour are strongly connected to the concept of so-called landscape affordances. The neologism *affordance*, first introduced by James Gibson in the late 1970s, describes the phenomenon of propositions emanating from objects within a specific environment (*Gibson 1979; Jung 2018; Loveland 1991*). Affordances are not (meta)physical properties, but rather empirical meanings that are in some way arranged in space (*Jung 2018*). Affordances were first introduced into archaeological discourse by Timothy Ingold in 1992 (*Gillings 2009; Ingold 1992; 2000*). In contrast to defining the components of the environment as passive resources, the concept of landscape affordances aligns dynamic and processual feedback with an individual's behaviour in the moment of mutual interaction (*Gillings 2009*). In a broader sense, these fundamentals are decisive for the differentiation of landscape and environment, which Ingold characterizes through objective and subjective or internal and external observers (*Ingold 2000; Meier 2017; Webster 1999*). Affordances are not a universal concept for certain actions of social groups with material objects or elements in their environment, but take place at the individual level of perception of an object in the immediate moment of its confrontation. According to David Webster (*1999*), the relationship between affordances and landscapes can be divided in two: low-order invariants denote the individual elements of a landscape, while high-order invariants summarize these elements and generate potentially available/not available or usable/not usable surfaces that are offered to an individual. Furthermore, Mark Gillings (*2007*) describes affordances as disposition properties which can be divided into direct and potential components. Nevertheless, both characteristics constantly coexist.

Although the concept of affordances is much older than the basic idea of GIS-based multivariate landscape reconstructions in archaeological research, both systems consist of similar components: the selection and categorization of environmental parameters and preferential sites in relation to the personal interests and actions of individuals in their environment. Preferences in land-use are not only physical interrelations between the needs and demands of people and their surroundings. According to Marcos Llobera (*1996; 2001*), changes in affordances reflect social changes within a group. Individuals in a particular group share common or similar structures, develop similar practices, and consequently share similar affordances.

A possible method for the reconstruction of human patterns in the landscape is the application of multivariate modelling. In landscape archaeology, multivariate modelling is based on the integration of a variety of GIS-based datasets (*Groenhuijzen 2019; Howey 2011; Howey, Brouwer Burg 2017; van Dinter 2013*). The inductive approach of multivariate landscape models is the recognition of specific location parameters in the archaeological dataset (*Güimil-Fariña, Parcero-Oubiña 2015; Weaverdyck 2019*). Digitally obtained integrative accumulative surfaces allow for the evaluation of environmental parameters without completely excluding human interactions. The diachronic reflection of the archaeological record of a study area helps to identify patterns and continuous human impacts on the landscape on large temporal and spatial scales.

Anthropogenic surface modifications – how modern is the past?

The French part of the Upper Rhine Valley was chosen as the study site. The area covers about 8300km^2 with large-scale geographical feedback and ecosystem connectivity (*Kempf 2019b*). In order to evaluate the natural conditions of the study area, the actual environmental conditions and the recent surface changes were modelled on the basis of historical maps, modern satellite images and various GIS-attributes and datasets. The whole region was massively modified by intensive land-use and increasing construction development within the past few decades. Climatic extreme events and long-term variability have also triggered droughts, flooding, and surface transformation (*Giacona* et al. *2018; Glaser* et al. *2010; 2012; Himmelsbach* et al. *2015a; 2015b*). The lowlands in particular are prone to increased temperatures, heat waves, and drought stress (*Duchne, Schneider 2005; Muthers* et al. *2017*).

For prehistoric societies it was periodic events that especially shaped perceptions and opportunities in the landscape. This means that the sum of spatial requirements is determined by the vulnerability of the environment to extreme events and the maximum benefit that can be assumed with an acceptable risk of loss. This results in a long-term trend in land-use which does not define areas of high suitability according to qualitative and modern standards, but is formed by periodic empirical values. Do pre-modern landscapes largely consist of experiences that are no longer accessible today? If this is the case, then the question arises to what extent today's surfaces are still parts of the physically existing landscapes of pre-modern societies, and how much palimpsest is still present in the landscape? A review of the environmental variability over the last 150 years is enough to identify the massive interventions in the ecosystem's balances. Large-scale infrastructure development, new urban areas, deforestation and expansion of arable land, drainage and exploitation of resources are just a selection of the anthropogenic impacts on the land surface. The rapid change in landcover can be tracked by comparing historical maps, modern satellite images from different years, and more recent landcover data sets such as Corine Landcover (CLC).

Material and methods

A Geographical Information System (GIS) is more than just a simple software tool for storing and manipulating spatial data. Much of the actual work that happens before visualization, spatial analysis and database management is the acquisition of spatial data that fits the desired spatio-temporal resolution of the research framework. The issues that were raised by the increasing application of GIS in interdisciplinary research led to the distinction between GIS (software tools) and GISc (Geographic Information Science), with the latter concerned with the many conceptual interrelationships between science and the humanities (*Conolly, Lake 2006*). Multivariate landscape analyses are based on selected and hypothetical environmental parameters. The selection of the parameters is carried out empirically via the feedback mechanisms of an ecosystem. For example, the type and composition of quaternary sediment stratigraphy in connection with groundwater height, flood risk and average precipitation rates determine soil formation processes and small-scale soil mosaics. From the estimation of the numerous (multivariate) determinants, a potential premodern landscape can be deduced (Fig. 1). In reality, however, this surface is based on modern empirical data and can only be transferred to prehistoric surface formations with considerable uncertainties. Nevertheless, these models allow us to draw conclusions about potential prehistoric land-use concepts, because they integrate ecosystem connectivity on both the small and the large scales. A broad variety of spatial and temporal environmental datasets have been acquired, manually developed or processed from various departments, institutions or through open source online portals. One major difficulty for the current study was the synchronization of datasets from the French and German sides of the Upper Rhine Valley, which have different geographical coordinate systems, spatio-temporal data resolution, typology, and particularly data availability and accessibility. The following descriptions list the respective datasets and briefly summarize the methods and strategies of the digital manipulations for the study area.

Environmental conditions

A comparison of a historical map from the 19th century with images from two satellite missions (Landsat-1, sensing date 9th October 1972; Landsat-OLI8 sensing date 24th September 2018) shows significant transformations of the surface cover during the past 150 years (Fig. 2). Massive deforestation activity took place that aimed to transform the surface into arable land or to be suitable for use as construction sites for increased urban and rural development. However, in order to understand the distribution of the archaeological sites in the landscape and consider the potential movement behaviour of past societies, landscapes need to be differentiated into their physical parameters such as climate, geology, and hydrology, and into their artificial and cultural components based on anthropogenic imprints.

Two surface classifications can be deduced from the evaluation of landcover changes and land-use: a landscape suitability model and a landscape bias model that evaluates the impact of modern surface transformations. These surfaces include geological units, soil quality and drainage potential, flooding vulnerability, groundwater level, and historical surface dynamics, such as infrastructure change, settlement expansion and modifications of the hydrological system. Based on these potential maps, archaeological and modern land-use patterns can be quantitatively compared and tested for their spatial interrelations. The environmental factors have been analysed on the supraregional scale to identify the large-scale connectivity patterns of the Upper Rhine ecosystem.

The geological and pedological data that supports the analyses of the study site were acquired from the Bundesanstalt für Geowissenschaften und Rohstoffe Hannover (BGR). For the French part of the Upper Rhine Valley, soil maps from the ARAA (Association pour la Relance Agronomique en Alsace, http://www.araa-agronomie.org/, last accessed 19th January 2019) and the API-AGRO (Paris, https://api-agro.eu/, last accessed 19th April 2019) were integrated in the GIS-project. The surface-near geological units are mostly dominated by Quaternary alluvial sedimentation of the River Rhine and River l'Ill. Soil formation processes and drainage potential are strongly linked to the height of the groundwater level below the surface, late Pleistocene and early Holocene loess cover, periodic flooding events, and sediment relocations that represent a conglomerate of different climatic and geomorphological components (*Hagedorn, Boenigk, 2008; Himmelsbach* et al. *2015a; Kempf 2018; 2019a; 2019b; Pfister* et al. *2006; Preusser 2008; Preusser* et al. *2016; Rentzel* et al. *2009*). Slope inclination and terrain roughness play a minor role in the study area, although the hydrological and geomorphological parameters are subject to natural transport, displacement and sedimentation processes, which are controlled by the gradient.

Two landscape models have been calculated from the multivariate environmental datasets. The first samples all information that is supposed to be deci-

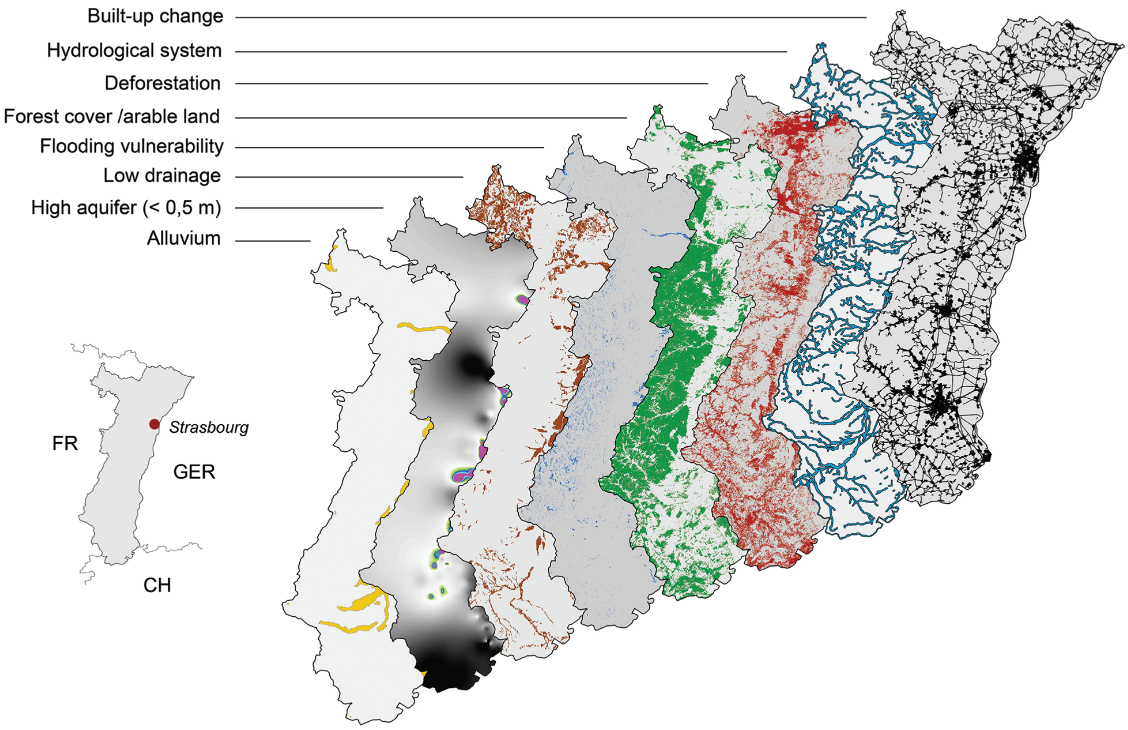


Fig. 1. Study area and single components of the multivariate environmental model. The Alsace is situated west of the River Rhine, stretching towards the Vosges mountains. Geological data (alluvial deposits) indicate fine-grained material, that lead to clayey-loamy soil conditions with low drainage potential. A high aquifer (processed and interpolated from 327 groundwater stations) and periodic flooding events (processed from Sentinel-1 SAR data from January 2018) lead to locally unfavourable surfaces. Forest coverage, agricultural exploitation, and increasing demand for arable land and infrastructural developments have had a significant impact on the surface over the past 150 years. The modern hydrological network is subject to manifold anthropogenic overprints such as canalization and drainage activities, which reshaped the environment and caused groundwater lowering and erosion.

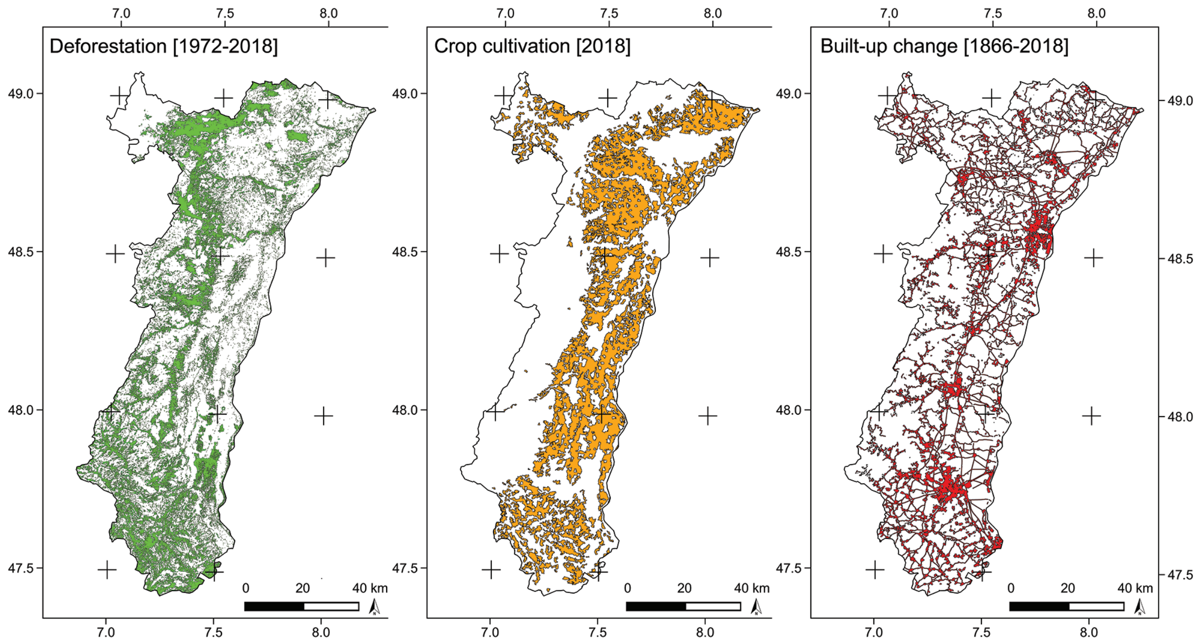


Fig. 2. Recent and historical landcover change and land-use in the study area based on various environmental datasets and remote sensing applications. Multispectral satellite imagery analysis and vegetation indices (NDVI) reveal massive deforestation processes between 1972 and 2018 (a), extensive crop cultivation (b), and strong built-up change (c).

sive for the choice of potential human utilization: adequate drainage potential, aquifer height below 0.5m, non-alluvial geology, very low-flooding vulnerability, and non-forested areas. The multivariate model generates six suitability classes from 5 (= very high surface suitability, all classes represent excellent surface and subsurface conditions) to 0 (= severe surface unsuitability, all classes represent severely unfavourable surface and subsurface conditions). The suitability model visualizes all environmental conditions that distinguish potential settlement and land-use corridors from areas with unsuitable surface and subsurface conditions based on the evaluation of their qualitative location factors.

The second model represents the modern biased surface conditions in the study area. The dominant parameters are deforestation, modern hydrological system, intense modern built-up change, and extensive agricultural utilization. The variables create a landscape model with five classes from 0 (= no modern bias) to 4 (= very strong bias).

Quantitative analysis of the archaeological record

The distribution of archaeological finds in the Alsace is used for the quantitative evaluation of land-use spread and bias through modern infrastructural construction activities. The spatial analysis is based on the consistent archaeological database that is provided by the Université de Strasbourg. The project ArkeoGIS is supported by over 170 international institutions and gathers archaeological data from all over the world (arkeogis.org) (*Bernard 2019*). Originally designed as a local open-source online GIS for the Upper Rhine Valley, the databases hosted by ArkeoGIS now include a vast amount of geospatial data, archaeological sites and environmental maps. Major advantages arise from the large amount of data for each respective archaeological period and continuous updates by Dr Loup Bernard (UMR 7044 ArcHiMedE, Université de Strasbourg). In particular, the chronological differentiation allows one to perform point pattern analyses that distinguish patterns pertaining to different chronological periods. The database contains a mixture of structured and unstructured data sets that require filtering in an information system (*Gattiglia 2015*). The fact that the database consists of both archaeological excavation data and archaeological survey data (including scattered and stray finds) poses a particular challenge for the interpretation of the spatial context of the data distribution. In particular survey data are characterized by the specific teleological research foci, the individual interests of the researcher, technical standards, and the site-specific conditions of the selected study area (*Cowley 2016; van Leusen 1996*).

For this research the stable versions of the open source software QGIS 2.18.6 and QGIS 3.6.0 (Open

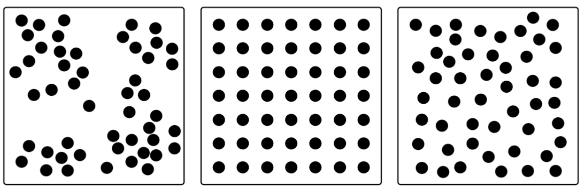
Source Geospatial Foundation Project, http://qgis.osgeo.org) which include GRASS GIS 7.2.0 and GRASS GIS 7.6.0 (Geographic Resources Analysis Support System, http://grass.osgeo.org) were used. The environmental modelling was supported by spatial statistical analyses conducted in R (R 3.5.1) and R Studio (R Studio 1.2.1335).

Point pattern analysis

Enrico Crema *et al.* (*2010.1118*) described point pattern analysis (PPA) as a method that "*examines the spatial configuration of point observations across a study area and, potentially, the underlying process behind its information*" (see also *Bevan, Conolly 2006; Conolly, Lake 2006*). The research in the Upper Rhine Valley relies on an archaeological dataset that consists of 10 726 sites that were tested for their clustered behaviour around modern agglomerations or along linear structures. In combination with Kernel Density Estimates (KDE) and Complete Spatial Randomness tests (CSR), PPA identifies the statistically significant characteristics of a dispersal of points/sites. A short explanation of the most important methods and tests follows.

Intensity analysis

Intensity analysis, also known as density analysis, is a method that allows one to describe the changing frequencies of observations in the data (*Conolly, Lake 2006; Herzog, Yépez 2013*). One way to produce intensity estimations is to describe the amount of observations in a geometrical area – usually a regular grid. The total amount of observations in each cell can be measured and interpolated from the cells to the entire study area (*Herzog, Yépez 2013*). The most common interpolation method is Kernel density estimation (KDE), which produces smooth visualizations of the point pattern distributions from the core areas and their surroundings (*Bonnier* et al. *2019; Conolly, Lake 2006*). A kernel – which can be visualized as a hill with a particular height, radius, and shape of slope – is placed over each point, and all of the kernels are added together to produce a density map, sometimes called a 'heat map'. In a GIS, KDE can be processed using the different radii (bandwidths) through which the density levels were processed (*Baxter, Beardah 1997; Herzog, Yépez 2013*). The radius, however, depends on the subjective research question and extent of the study area (*Bonnier* et al. *2019; Brigand, Weller 2018; Hughes* et al. *2018*).



Clustered | Regularly dispersed | Random

Fig. 3. Three spatial point patterns: Clustered, regularly dispersed, and random distributions of 49 points.

Complete Spatial Randomness (CSR) and Ripley's K-function

Spatial point pattern analysis examines the dependence between points. The difference with typical point analysis is the inclusion of spatial attributes in a model. The character of the spatial behaviour of point patterns is among the first statistical analyses that are conducted to identify clustering, regular, or dispersed point distribution patterns (Fig. 3). Typically, so-called CSR- tests (Complete Spatial Randomness) are applied to compare spatial point patterns to complete spatial random processes (*Lucio, Castelucio de Brito 2004*).

Oliver Nakoinz and Daniel Knitter (*2016*) pointed out that CSR-tests allow not only for the detection of random distributions but also of regular point (negative interaction) and clustered point distributions (positive interaction). Points do not behave equally at all scales. At smaller scales, they can show clustered behaviour that gets random or dispersed at larger scales. If the spatial pattern is not clustered, it is either random or regularly dispersed. However, the regular distribution of anthropogenic or ecological samples is very rare (*Haase 1995*). One of the most useful statistical approaches to test CSR is Ripley's K-function (*Bevan, Conolly 2006; Conolly, Lake 2006*) that describes how point patterns are distributed over a certain area (*Dixon 2002*). Ripley's K defines the radius at which clustered behaviour is established. Broadly speaking, the function counts the number of points within given distances around each point and compares the result to the number of points one would expect within a totally random point distribution. If the number of empirically observed points within a certain distance is greater than the number of the simulated random distribution, the empirical point pattern is clustered at that scale. If the number is smaller than the simulation, the distribution is dispersed (*Dixon 2002*).

PPA was conducted in the study area to estimate the spatial behaviour of the archaeological record and the spatial relationship between the record and the modern agglomerations (Fig. 4). First, a grid of 10 x 10km was established across the research area and

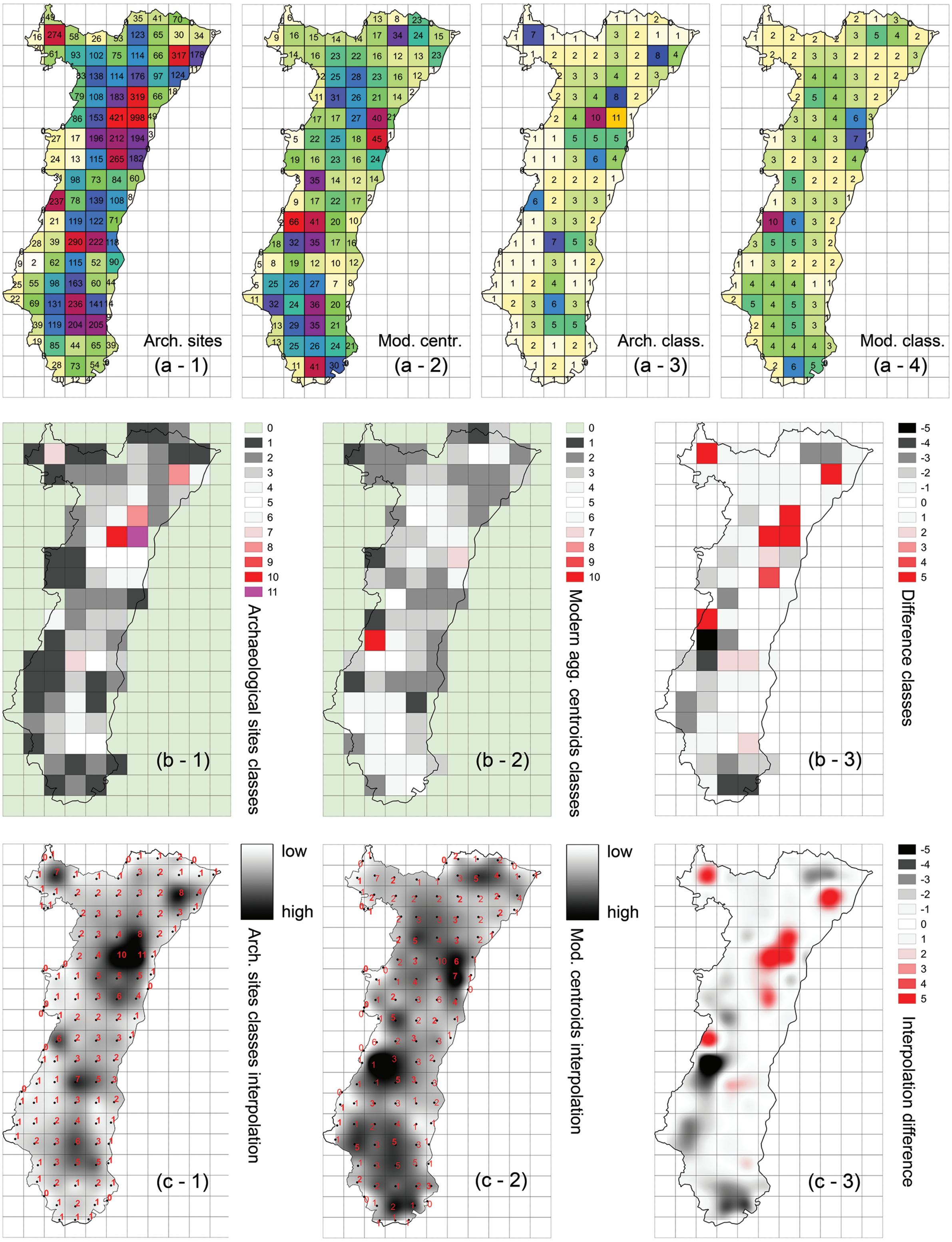


Fig. 4. Point pattern analysis and interpolated density estimates of the site distribution of archaeological sites and modern agglomeration centroids. (a–1) total count of archaeological sites in a 10 x10km grid; (a–2) modern agglomeration centroids in the same grid. The total number of sites was classified in categories 1–10 (11) with 1 = low number of sites and 10 = high number of sites, and 11 for the outlier value of 998 sites (a–3, a–4). These reclassified values were assigned to cells in a raster (b–1, b–2) and the differences between both data sets were calculated (b–3). Multilevel b-spline interpolations of these reclassified values (c–1, c–2) and the differences between them were calculated to visualize areas of congruence (c–3, moderate values) and difference (c–3, extreme negative and positive values).

the total number of archaeological sites and modern agglomeration centroids were calculated for each grid cell. The numbers were reclassified in ranges from 1 to 10 and one outlier 11 (the area of Strasbourg with 998 archaeological sites in the grid cell). The reclassified values were mapped accordingly (Fig. 4a). From the reclassification, a raster analysis was performed that attaches the number of recorded sites to every grid cell. The difference between the archaeological and modern raster indicates the high spatial interdependencies of the archaeological sites and the modern agglomerations (low values, –1, 0, 1, white signature in Fig. 4b-3). Areas that are significantly different show high negative or high positive values. From the raster, a multilevel b-spline interpolation was used to produce a density plot with smoothed value ranges (Fig. 4c–1,c–2). Finally, the difference calculation quantifies the spatial relationship estimate of both datasets in the study area.

Furthermore, a KDE estimation was performed for both datasets with r=10 000m (Fig. 5b) for the modern agglomeration centroid dataset and r = 5000m for the archaeological sites (Fig. 5a). Thresholds have been calculated to classify the results of the KDE and enhance their visual intelligibility. Both analyses indicate spatial interdependencies between the datasets. However, significant outliers are visible that are caused by extreme values in the point pattern distribution.

Results and discussion

In the Alsace, the bias model reveals a very strong relationship between the spatial distribution of the archaeological record and the modern residential and industrial areas (Fig. 6). To refine the model, the modern agglomeration boundaries were separated into small residential districts, local industrial areas, and rural complexes. The centroid of every modern built-up complex was calculated (n = 1913) and analysed according to the methods applied to the archaeological database. Most of the sites of both datasets are situated in areas that experienced strong surface transformation. Figure 6 shows the spatial relationship between the distribution of modern residential areas, the archaeological sites, and the accumulative bias surface in the study area. The bias surface was calculated from built-up change, deforestation, modern arable land-use, and the connection to the modern hydrological network. Five bias classes have been deduced from the accumulative

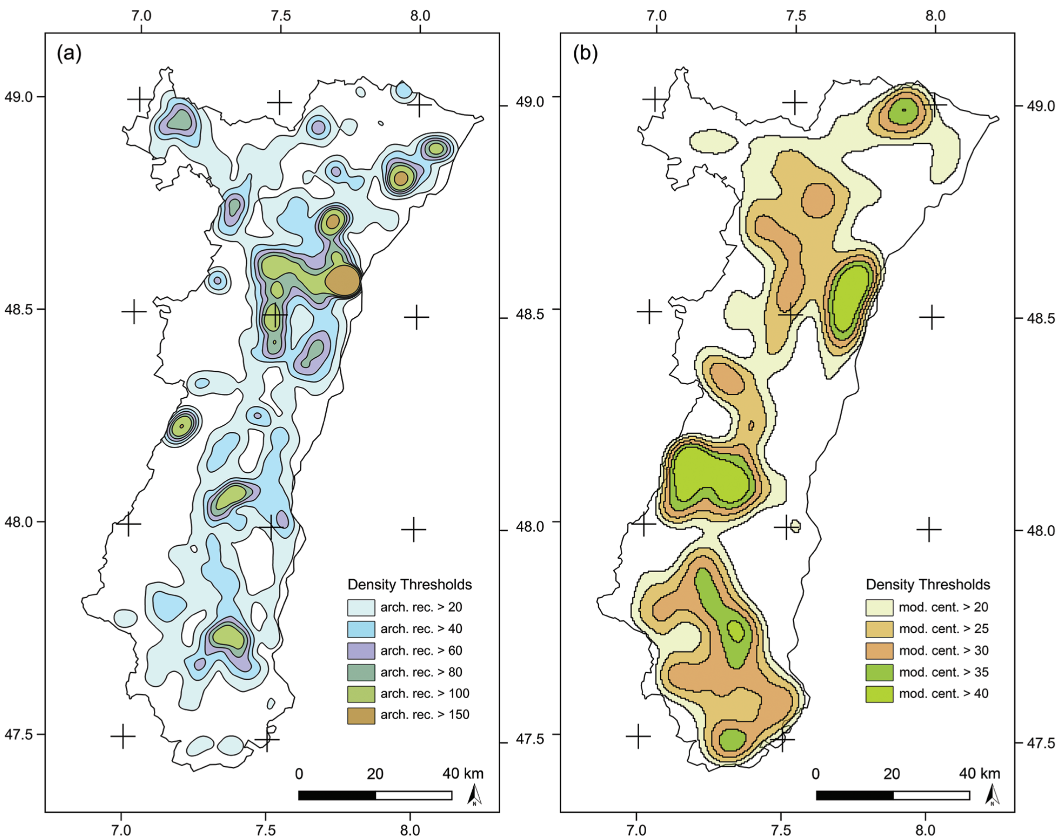


Fig. 5. Density estimates (KDE) of (a) the archaeological sites (r = 5000m, n = 10 726) and (b) the modern agglomeration centroids (r = 10 000m, n = 1913).

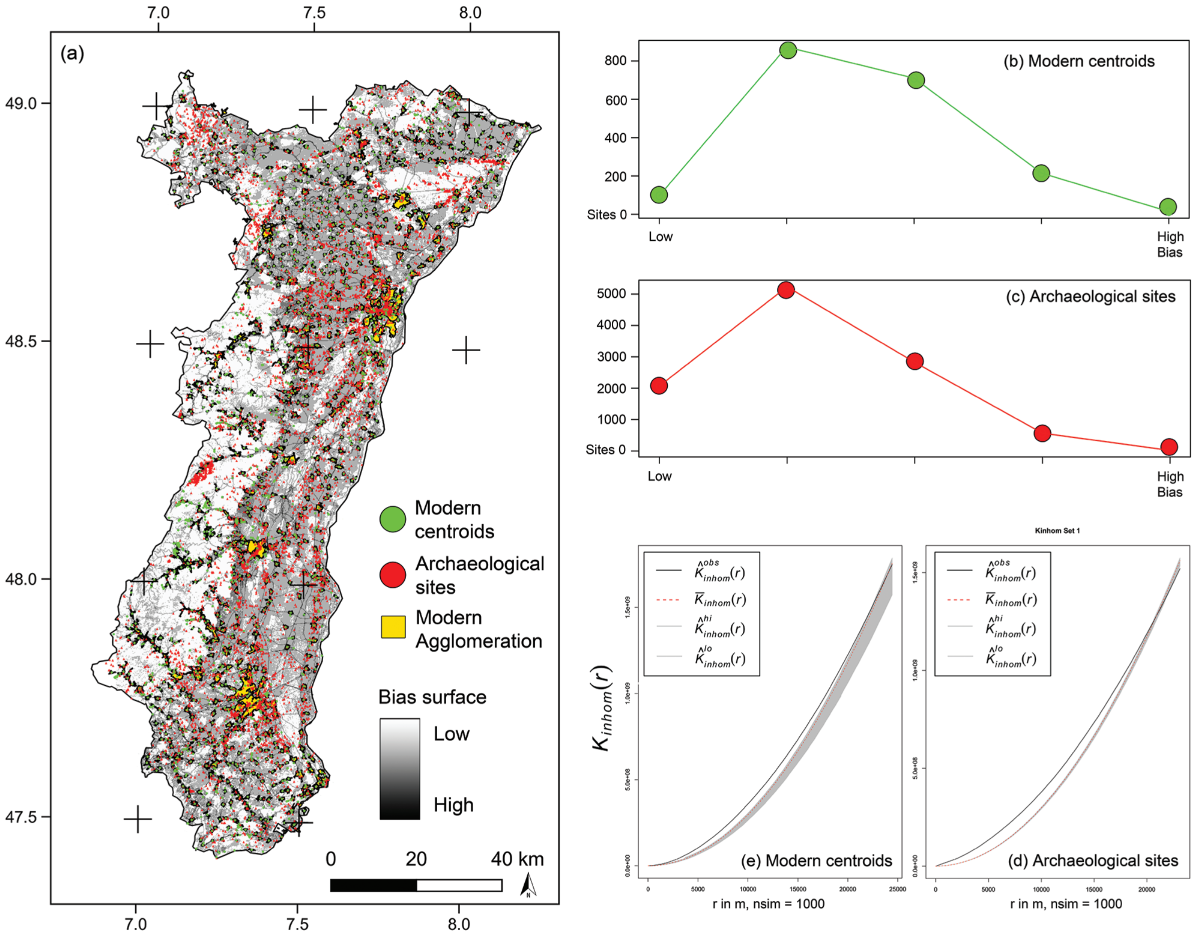


Fig. 6. Bias model from built-up change, deforestation, and the modern hydrological network in the Alsace (a). Bright areas show low bias intensity, dark areas high bias intensity. Modern agglomerations (green) and the archaeological record (red) are modelled to estimate the bias value of each site (b, c). Both site distributions show clustered spatial behaviour and are not randomly dispersed (e, f).

surfaces, which classify the influence of modern use from low to high. The distribution of archaeological sites and modern agglomeration centres modelled on the bias surface enables the estimation of similar spatial behaviour. The distribution patterns of modern agglomerations indicate that a few centres do not show any biased values. This is because modern urban development and new construction sites hardly interfere with the historical village centres. The distribution of archaeological finds is similar to that of modern agglomerations. Twenty percent of the archaeological finds show little or no impact from modern land-use. This may be because the archaeological database includes medieval and early modern heritage sites, which are located in the historical centres outside the bias categories. However, 80% of the total archaeological record lies in the biased categories. The datasets have further been analysed using Ripley's k-function to test CSR (Fig. 6e,f). The results reveal significant clustering, and a random distribution can be excluded. This supports the argument for a strong spatial relationship between the two site distributions.

These estimates indicate intensive location relationships between modern development, geomorphology, vegetation cover, land use, and the distribution of archaeological sites. Due to the similar spatial behaviour of settlement centres and archaeological sites, the hypothesis is pursued that modern construction activity is the decisive factor in the perception of archaeological concentration areas. For this reason, Thiessen/Voronoi polygons were calculated and analysed for their size and the spatial relationships with the archaeological record. The polygons are not randomly distributed over the area and their size is strongly linked to the highest modern built-up density and the most intensive construction activity (for example, in the agglomerations of Strasbourg). Intensively restructured areas represent a small network of polygons, while rural areas are characterized by larger polygons. The archaeological sites are homogeneously distributed in the polygons. Only a few polygons show extreme values (the agglomerations of Strasbourg). Most of the sites are situated in small urban and rural agglomerations. There is no significant correlation between increasing polygon size and an increasing number of archaeological sites. The observations from the K-function are supported by the analyses of the spatial patterns of the modern centroid Thiessen/Voronoi polygons in relation to the archaeological record. The distribution indicates non-regularly dispersed site distribution (Fig. 7).

Furthermore, the land-use potentials of the region were analysed to evaluate continuous site occupation. The multivariate suitability model described above was used as a basis for the spatial analysis of both datasets (Fig. 8). Both site distributions show similar patterns. The modern agglomerations and the archaeological record are distributed within the highest classes of the model (Fig. 8b,c). Ninety-two percent of the modern settlement and built-up centroids are located in the two highest suitability categories. The site dispersal decreases significantly within the other ranges. A similar signal can be detected in the archaeological record: 91% of the total archaeological finds lie in the highest two categories, with a sharp decrease in the numbers in the others. An additional distance matrix was calculated to demonstrate the strong spatial relationship between archaeological sites and modern agglomeration. This reveals that the closer to an urban or rural agglomeration an area is, the more archaeological sites can be recorded. The significance is further increased if

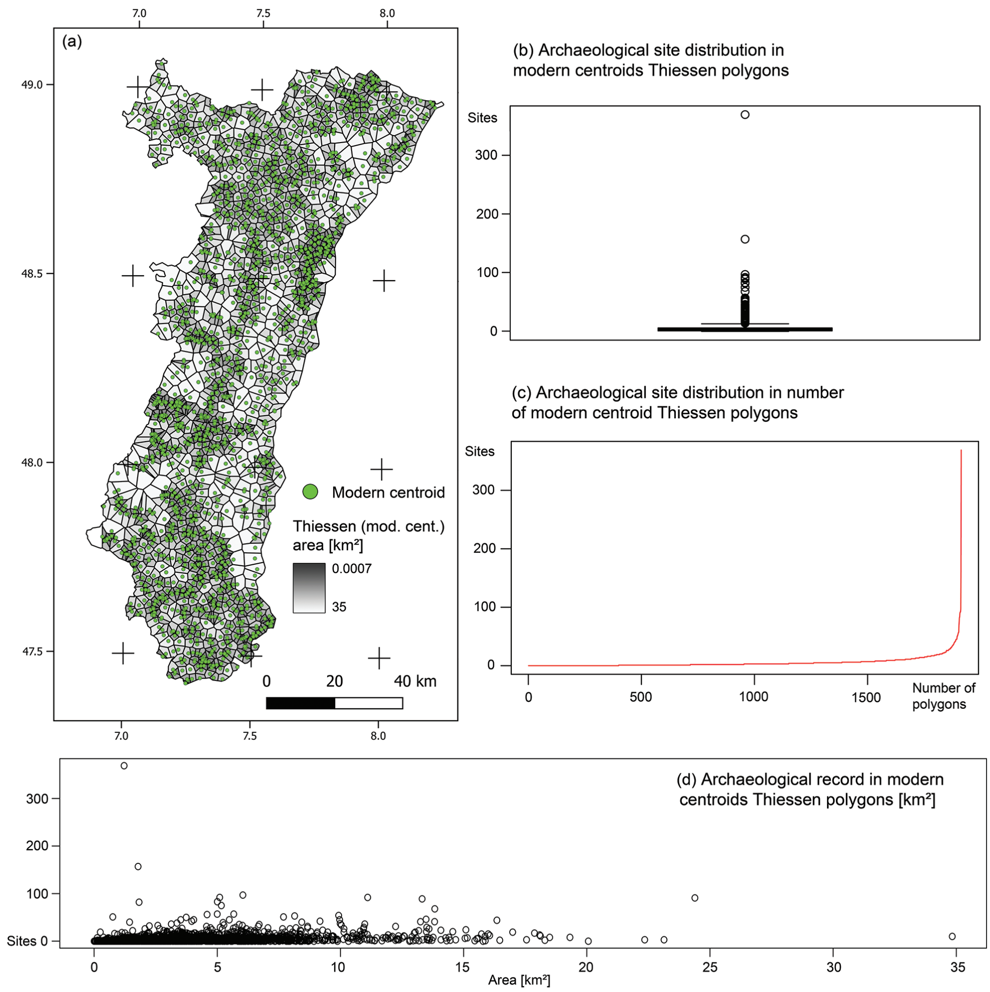


Fig. 7. Calculated Thiessen polygons from modern rural and urban agglomeration centroids (a). The size varies from 0.0007km² to 35km² in the study area. Small polygons indicate high population density (high modern residential area density). The archaeological sites are homogeneously distributed in the polygons with only a few outliers caused by archaeological site concentrations in the area of Strasbourg (b, c). The polygons show clustered spatial behaviour and only a few polygons reach up to more than 15km² (d). Most of the sites are situated in small urban and rural agglomerations. There is no significant correlation between increasing polygon size and increasing number of archaeological sites.

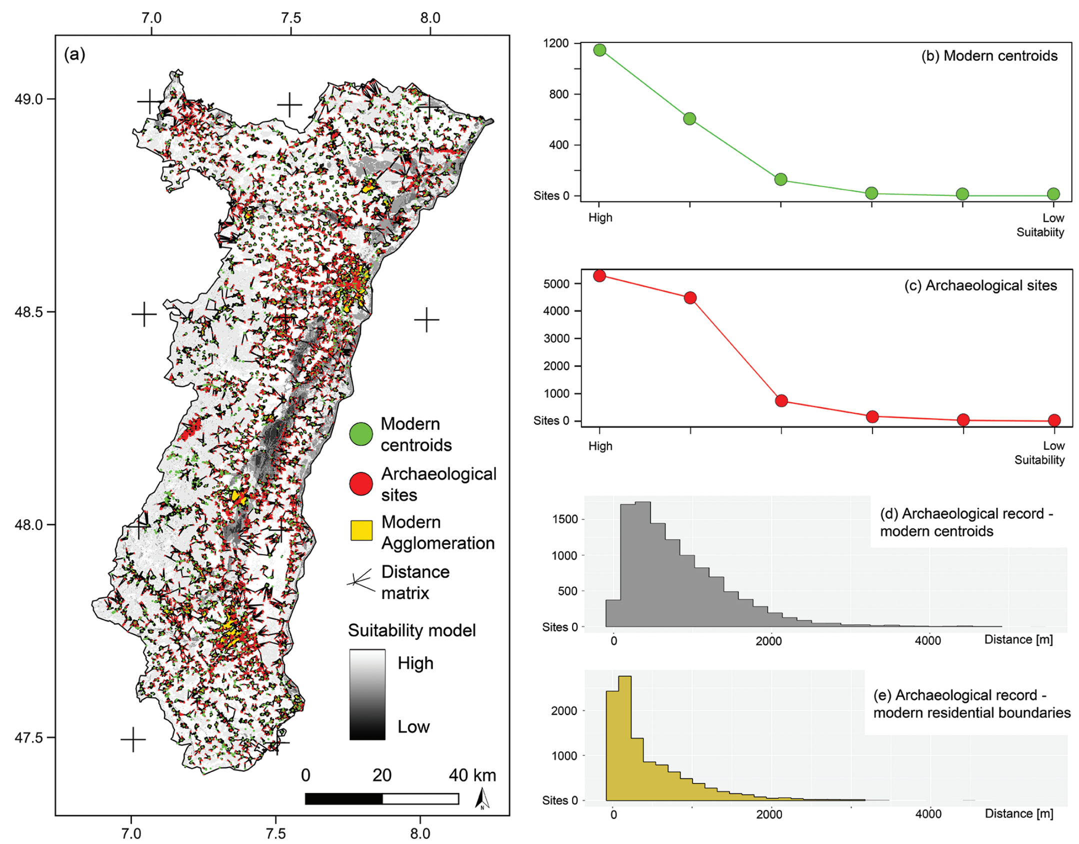


Fig. 8. Multivariate landscape suitability model (a) composed of soil quality, geological units, low flood vulnerability, high drainage potential and low aquifer (no groundwater discharge). Based on the model, the distribution of modern agglomerations (n = 1913) was analysed. (b) A total of 1161 sites are located in very high and 607 in high suitability classes. The total archaeological record (n = 10 726) shows 5299 sites in very high and 4485 sites in high suitability classes (c). The distance matrix between the archaeological record and the modern agglomerations (d, e) demonstrates that most archaeological sites are located in close proximity to the nearest modern rural or urban agglomeration centroids (d). Modelling the distance between the archaeological record and the boundaries of the modern residential polygons further increases the significance (e).

the distance matrix is based on the residential boundaries (polygon) instead of the centroids (Fig. 8d,e).

The interrelationships are not only visually and spatially significant, but also statistically. Modern land-use influences our perception of the distribution of archaeological finds in the landscape. There are several reasons for this: first, it is possible that the study area has experienced continuous utilization and the archaeological sites are located where continuous land-use takes place. This would support the theory of constant settlement and land-use strategies, and ignore dynamic environmental and socio-cultural behaviour for several thousand years. Such hypotheses are currently questioned by geologists and Quaternary sedimentologists that are evaluating the palaeochannel shifts and riverbed relocations of the Upper Rhine during the Holocene (*Rambeau* et al. *2019*). The first results indicate strong displacements of the Rhine course and its tributaries – over the entire Holocene. According to the authors, largely stable conditions of the fluvial system of the river Rhine can only be assumed for the post-Roman period onwards – at least for the investigated parts of the river course. Local settlement continuity can only be assumed for the margins of the higher mountain foreland and elevated Mesozoic plateaus in the floodplain. The floodplain of the Holocene anastomosing river periodically shifted, and erosion and accumulation processes replaced each other in very dynamic systems that still seem to be unconsidered in landscape archaeology.

However, a reasonable question here is whether the suitability model is biased by modern perceptions of the landscape. Entire past landscapes cannot be reconstructed because past cognitive concepts of how landscapes were formed cannot be perceived by modern individuals. Premodern landscapes consist of experiences, traditional values and ideas rather than their actual geographical contents (*Gramsch 1996*). The landscape palimpsests of a variety of cultural human-environment interactions have led to a massive transformation of the earth's surface, and eventually to the outlook of the modern world. All archaeological distribution is finally a modern perception of how we interpret past human behaviour. This is triggered through modern urban agglomerations and the pull-factor of continuously inhabited regions. Intensive survey activity generates a high archaeological density in these areas, while adjacent areas show a low data volume due to lower survey intensity. Archaeological corridors are created technically and methodically (*Armit* et al. *2014; van Leusen 1996; van Leusen, Kamermans 2011*). The major bias factor is the vicinity to modern built-up areas, and in particular intensive construction activity in the marginal zones of urban agglomerations, extensive infrastructure and rail tracks. Furthermore, cultural heritage sites in historical centres are important public pillars that acquire increased cultural perceptions. Well-organized monument preservation management and a high density of excavation companies increases the capability to undertake archaeological surveys and prospections what strengthens public recognition and financial support – in addition to the benefits of potential scientific publication.

Conclusion

Simple distribution maps of archaeological data are useless. They produce dehumanized patterns in artificial space. The strength of GIS in archaeology is its diversity (*Conolly, Lake 2006*). The process behind the application of GIS, or digital modelling in general, is not meant to stand opposed to the interpretation of human patterns, but rather to complement and extend the approaches of a comprehensive and modern landscape archaeology (*Llobera 2012*). Just like in any other science, uncertainties are a fundamental property of progress and research development, and archaeological data in particular can easily be confused with absolute data. However, it is the current state of archaeological research that is used to model the spatial behaviour of past societies. The results of the bias and suitability models of the Alsatian Upper Rhine can be used to identify continuously used areas of intense human activity. On the other hand, they can also be used to estimate the impact of modern landcover change on the (modern) archaeological distribution, and thus to engage in methodological source criticism. This paper shows that there are very significant relationships between modern anthropogenic surface modifications and the density of the archaeological record that is perceived by individuals today. Past societies did not leave traces in linear patterns. The perception of cultural heritage is constructed by modern individuals moving in space. The actual archaeological traces were constructed by individuals creating space. That difference can be an additional way to understand past human-environment interactions.

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