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PREDICTIVE SPATIAL MODELLING

Philip Verhagen and Thomas G. Whitley

Introduction

Archaeological predictive modelling can be defined as a set of techniques employed to predict "the location of archaeological sites or materials in a region, based either on a sample of that region or on fundamental notions concerning human behavior" (Kohler & Parker, 1986, p. 400). The basic premise of predictive modelling is that human spatial behaviour is to a large extent predictable, which implies that the locations where people lived and performed their daily activities can be identified on the basis of statistical and/or explanatory models.

The roots of predictive modelling can be traced back to the days of New Archaeology, and in particular the development of Site Catchment Analysis in the 1970s (Vita-Finzi & Higgs, 1970). Archaeologists became aware that human settlement is intimately linked to its environmental setting, which also implied that it should be possible to predict the locations suitable for human settlement. Around the same time, Cultural Resource Management (CRM) was developing in North America through legislation aimed at the protection of cultural heritage. In the absence of sufficient data to identify all archaeological sites in a region, predictive modelling answered the need for a more comprehensive mapping of cultural resources and ways in which to avoid impacts to them by development. Although mainframe-based Geographic Information Systems (GIS) had already been applied to predictive modelling in a very limited fashion, the arrival of desktop-based GIS in the late 1980s paved the way for further proliferation of predictive modelling, particularly in CRM contexts. Publication of seminal works on the theory and methods of predictive modelling began initially in the USA (Kohler & Parker, 1986; Judge & Sebastian, 1988) and later also in Europe (Van Leusen & Kamermans, 2005).

Predictive modelling is used in archaeology for two purposes. First, it is a planning aid for CRM in order to assess the risks of disturbing archaeological remains during development projects. Here predictive models serve to inform and influence the decision-making processes of planners and to convince them that developments should take place in the least sensitive areas. They also guide the archaeological investigations once developments have started, by making reasoned choices on where to concentrate research efforts within the constraints of available time and money. The cost-effectiveness of the approach has been proven in CRM, and it has provided a basic degree of protection to zones of high archaeological potential in those regions where it is included in CRM policies. Second, predictive modelling is applied as a tool to develop and test scientific models of human locational behaviour. In academic contexts, therefore, predictive models can be considered as heuristic devices (Verhagen & Whitley, 2012) that can play an important role in formalizing and quantifying theoretical notions on the development of settlement patterns and land use.

Despite its widespread application, predictive modelling has also encountered substantial criticism from archaeologists. This is because it will never be able to accurately predict the locations or presence of all archaeological remains. The models are only as good as the data and theories that have been used to create them, since we can only extrapolate from the existing state of archaeological knowledge. In that respect, there is no real difference between theory-driven or data-driven approaches; they both reflect our existing understandings, or biases, about the human past. For many archaeologists the risk of 'wrong predictions' and their undesired consequences for the protection and investigation of the archaeological record in CRM is unacceptable. From a scientific point of view, however, discrepancies between prediction and data can be the starting point to develop new theories about site location and/or to direct future data collection practices, which could also be a guiding principle for decision making in CRM.

Method

Predictive models can be made following two different strategies, usually named 'inductive' and 'deductive' (Kamermans & Wansleeben, 1999), but more accurately described as 'data-driven' and 'theory-driven' (Wheatley & Gillings, 2002). In data-driven modelling, the locations of known archaeological sites in a study region are compared to a number of parameters that are considered to be important to settlement choice (such as slope gradient, soil type, or distance to water), using various statistical assessments within a GIS. The results of this quantitative site location analysis can then be extrapolated to areas where no archaeological data are yet available, and will thus result in a prediction of site densities or probabilities for the area to be studied. A popular technique for data-driven predictive modelling is logistic regression (cf. Warren, 1990; Hudak et al., 2002; Conolly & Lake, 2006, Chapter 8.8). This is a technique for fitting a prediction curve to a set of observations that is especially suited for variables that are measured at different scales (nominal, ordinal, interval and/or ratio). Also, fitting to a logistic rather than to a linear curve has advantages for increasing the statistical contrast between site and non-site locations (Warren & Asch, 2000), and as such it has been the preferred tool for predictive modelling for many years. However, many other options are becoming available, including ecological niche modelling (cf. Kondo, 2015; Banks, 2017), Monte Carlo simulations (cf. Kvamme, 1997; Vanacker et al., 2001) and Bayesian statistics (cf. Finke, Meylemans, & Van de Wauw, 2008; Van Leusen, Millard, & Ducke, 2009).

Despite the current state of sophistication of statistical modelling, it is still very difficult to determine which statistical technique performs best since there are hardly any case studies available where methods are compared. Additionally, regression and similar statistical analyses require large datasets of previously known archaeological sites to produce significant results. Therefore, only well-represented site types or behaviours can be predicted using such techniques, and prior biases in those datasets dramatically affect the outcomes.

The theory-driven approach bypasses most of the statistical complexity by defining theoretical assumptions about the parameters influencing human spatial behaviour. For example, it can be assumed that early farming communities preferentially located their settlements in environments well-suited for agriculture and animal husbandry, which in turn can be related to parameters such as soil quality and texture, nitrogen content, and moisture potential or drainage. Those characteristics may be embodied in, and extracted from, soil type classifications which exist within a GIS dataset. Weights are then given to the parameters based on the nature of the assumptions about the people who may have been living there, as well as different site functions or behaviours. The weights and variables are then combined into predictive formulas which are compared to the known archaeological record in order to judge their performance. This approach has the advantage of including more sophisticated theoretical frameworks that are based on causal explanation; it can include human agency as a factor, and it is not directly dependent on archaeological datasets (Verhagen & Whitley, 2012). As a result, there are few restrictions on the types of sites or behaviours which might be predicted. Deciding on a best possible model however still implies comparing various parameter weights to the actual archaeological data.

Problems and pitfalls

The potential flaws of predictive models were summarized by Van Leusen and Kamermans (2005):

1. the archaeological input data is usually not representative of the full archaeological record, and the archaeological record itself is a biased reflection of human activity in the past; therefore, we cannot expect that models based on existing archaeological datasets will accurately predict all locations of past human settlement;
2. the predictor variables used are often based on modern-day environmental datasets, that may not be at the right level of detail and accuracy for predictive modelling purposes, and may not accurately reflect the situation in the past;
3. socio-cultural variables are usually not included;
4. the temporal resolution of predictive models is limited, since this is determined by the archaeological and environmental input datasets used; and
5. testing of predictive models is often done in a haphazard way and in most cases does not involve a representative field survey; the distinction made between areas of low and high probability has instead often led to a policy of not surveying the low-probability zones, and in this way, a self-fulfilling prophecy will be created (Wheatley, 2004).

Predictive modelling has often been criticized for restricting itself to a limited set of 'environmental' variables. This can partly be attributed to the fact that there are relatively few relevant datasets available that cover large areas. The inputs most often used are derivatives of Digital Elevation Models (in particular slope and aspect), and, to a lesser extent, topographical, geological and pedological maps. This approach has been successfully applied in many cases, but the datasets are sometimes used in a very uncritical way. Socio-cultural variables (such as distance to roads, or to specific archaeological sites), on the other hand, are much more difficult to implement in predictive models because of the scarcity of relevant data and lack of quantifiable theoretical models, although there is no inherent barrier to including them (see e.g. Whitley, Moore, Goel, & Jackson, 2010).

Ideally, the desired degree of accuracy of a predictive model should determine what is needed in terms of data and knowledge. In practice, however, predictive models are often made on the basis of datasets that happen to be available, and for this reason they can vary considerably in their accuracy. It is therefore extremely important that the models are tested, both internally in order to establish the uncertainties in the parameters and archaeological data used by means of sensitivity analysis, and externally by adding independent, representative archaeological data. Establishing the representativeness of archaeological datasets however is often very difficult, since in many cases there is insufficient information about the intensity and methods of survey applied and about the influence of potential biases, such as the visibility of archaeological remains on the surface. These factors highly influence not just the number of archaeological sites found but also the types of sites that can be discovered successfully (Verhagen, 2008).

Creating and testing archaeological predictive models is therefore a complex exercise, at the end of which the results need to be translated into terms that can be easily implemented in CRM and other planning contexts. Formal statistical assessments do not necessarily play an important role in this. Instead, a number of explicit and implicit assumptions about the importance of specific archaeological remains, their state of preservation, and the costs of excavating them are used as well to assess the archaeological and financial risks of development plans. Thus, creating predictive models is only one stage in the decision-making process surrounding archaeology in spatial planning, and as such their role in CRM should not be overemphasized. However, since they are used at the beginning of the planning process and will direct decision making in subsequent stages, their accuracy should be a major concern to archaeologists, developers and planners alike.

Case studies

The Mn/Model

A classic example of large-scale agency-supported predictive modelling is known as the 'Minnesota Model' (or Mn/Model in abbreviation – Hudak et al., 2002). The Mn/Model was the first archaeological predictive model to be applied to an entire US state, and was originally initiated in 1995 by the Minnesota Department of Transportation with the financial support of the US Federal Highway Administration. It was also the first widely applied, data-driven model to consider survey bias and depth of deposits in its application.

The main objective of the Mn/Model was to provide transportation planners with a GIS-based tool that would help them identify areas likely to contain archaeological sites, so that they could be avoided. The idea was that these sites could be identified early on in the planning process, thereby saving time and expense later on when transportation projects were underway. The primary methodological assumptions of the model were:

1. That only pre-1837 sites could be predicted using the methods employed. The year 1837 marks the earliest permanent historic-era settlement within Minnesota, and it was largely assumed that historic Euro-American settlement followed more complex patterns not defined by environmental variables.
2. That separate models were necessary for 24 different 'environmental regions' within Minnesota. Each region was defined based on topographic distinctions, ecological communities, or geomorphological origins. They each also had a unique set of pre-existing archaeological sites from which the correlative analyses were drawn.
3. That paleo-landscape and geomorphological modelling would additionally help create the 'third and fourth' dimensions of depth and time to the analysis.
4. That issues with sample size and pre-existing survey bias could be overcome by using statistical techniques. These techniques would allow the generation of appropriate datasets from which correlations could be derived.

The Mn/Model is a set of 24 multiple logistic regression models (one for each environmental subregion) that each identify correlations between a dependent variable (e.g. site presence/absence) and a wide range of independent variables (the environmental predictors). In this case, predictor variables were derived from elevation, watersheds, hydrology, soils, geology, vegetation maps, anthropogenic disturbances (usually modern), paleoclimate models of temperature, precipitation, geomorphological events, and palynology, as well as some historical cultural features in limited contexts (Hudak et al., 2002). Known site locations were evaluated against 'non-sites' using these variables in a logistic regression analysis for each environmental region over three successive phases; each modified in response to data quality or other issues encountered during the process.

The resulting regional models met or exceeded the performance expected by the modellers, with an average gain statistic (cf. Kvamme, 1988) of about 0.71 for all regions combined during Phase 3, which had improved from 0.37 in Phase 1, and 0.68 in Phase 2. That range of individual gain statistics though varied widely across regions with some as low as 0.40 and others as high as 0.89 depending on the number of sites being modelled and the ability of the model to reduce the size of the high/medium probability areas.

Gain is calculated as follows (Kvamme, 1988):

$$G = 1 - p_a / p_s$$

where
p_a = the area proportion of the zone of interest (usually the zone of high probability); and
p_s = the proportion of sites found in the zone of interest.

If the area likely to contain sites in a region is small (the model is very precise), and the sites found in that area represent a large proportion of the total (the model is very accurate), then we will have a model with a high gain.

The authors note that the positive results in some cases can be very misleading due to biased survey, few known sites in limited environments, and very few actual surveys having been conducted. Its total cost over a period of seven years was \$4.5 million. Nevertheless, the Mn/Model has been held up as a successful application of archaeological predictive modelling since it is estimated to have saved the State of Minnesota about \$3 million per year, for the first four years of its implementation. Several other states have followed with their own statewide data-driven archaeological predictive models including North Carolina and Washington.

The LAMAP approach

The most popular methods for probabilistic predictive modelling of unrecorded site locations – logistic regression and weights-of-evidence modelling – are not well suited for dealing with site presence-only data. Unfortunately, many archaeological survey data sets have little or no information on site absence, and predictions are then usually made using 'pseudo-absence' data, by assuming that the prevalence of non-sites is approximately equal to a random or uniform distribution over the whole study region. This is justified by the argument that the proportion of sites compared to non-sites is very small, and thus the prevalence of non-sites will be very similar to such a random or uniform distribution (Kvamme, 1988).

Carleton, Conolly, and Iannone (2012) and Carleton et al. (2017) instead defined the notion of archaeological potential as 'the relative suitability of different land parcels within a confined region for human occupation', a measure that can be estimated from site presence-only data. A similar concept is applied for expert-judgment based predictive models in the Netherlands (see Van Leusen & Kamermans, 2005), but these do not include quantitative estimations.

The underlying theoretical concept assumes that, when deciding where to settle, people will preferentially select the best of the available options using 'mental archetypes' from nearby areas. So locations that are more similar to nearby sites will be more likely to be settled than other ones. The mental archetypes themselves are not directly accessible, but since existing sites are realizations of these archetypes, it can be assumed that their characteristics can be used for predictive modelling purposes by finding the locations that are most similar to them.

The authors developed a new methodology for this purpose, the Locally Adaptive Model of Archaeological Potential (LAMAP), that employs not just the information from a site's location itself, but from a predefined (circular) neighbourhood around the site. The characteristics of these known site location surroundings are then compared to the whole study region, resulting in a measure of similarity of each location in the region to the characteristics of the known sites. Such an approach is not completely new: similar GIS-based analyses had already been undertaken extensively in the south of France since the 1990s (see Favory, Nuninger, & Sanders, 2012). However, these were not aimed at predictive modelling but only at analysing site location preferences.

The LAMAP method is implemented by first calculating the frequency of each particular value of a landscape characteristic, like elevation, within a neighbourhood around a site. Optionally, the model accommodates distance weighting, so that locations closer to the site will be considered as more important than those further away. Then, it is established how probable it is that the observed set of values that occurs jointly within the site's neighbourhood is also found elsewhere.

Carleton et al. (2012) first prepared a test model for a set of Maya sites in Belize, using a conventional set of environmental parameters and a distance radius of 1 km. The model's performance, measured with Kvamme's gain statistic, was considered to be good, although the testing was only done by holding back a portion of the site sample (*split sampling*; see Kvamme, 1988, for more details). Later, they also tested the model using new field survey data and sites newly identified on Light Detection and Ranging (LiDAR) images (Carleton et al., 2017). This resulted in a very close correlation between prediction and site occurrence. The high success rate coupled to the relatively simple implementation suggests that this method is a good solution for data-driven predictive modelling on the basis of site presence-only data without having to resort to using pseudo-absence data.

Georgia Coast Model

In response to the overwhelming number of predictive models that are based on biased datasets and rely on a data-driven approach, Whitley (2003, 2005, 2010) addressed ideas of causality and determinism in predictive modelling and the misleading use of the gain statistic as the sole measure of model success. His approach to a theory-driven model was one based on examining human energetics, or the idea that all human behaviour entails maintaining a balance between energy costs and expenditure, and that site 'selection' was a cognitive process based on the applications of both choice and risk. To that end, he initiated the Georgia Coast Model in 2009, as part of a large-scale analysis of the collection, storage, trade, and consumption of faunal and floral resources in the coastal region of the US state of Georgia between 4500 and 300 BP (Whitley et al., 2010; Whitley, 2013). The goal was not to create a predictive model per se, but to use geospatial analysis, driven by theory, to develop explanations for why certain areas may have been chosen for settlement.

Rather than predict the locations of archaeological sites, the energetics approach was to predict the locations of faunal and floral resources during different seasons and over long periods, as well as modelling other environmental variables that limited the availability of, or access to, those resources. The approach relies on key concepts from Optimal Foraging theory (MacArthur & Pianka, 1966; Emlen, 1966), Central Place Foraging (Orians & Pearson, 1979; Stephens & Krebs, 1986), as well as Diet Breadth (Hames & Vickers, 1982; O'Connell & Hawkes, 1984; Winterhalder and Kennett, 2006; Smith, 1991; Grayson & Delpech, 1998) and Prospect theories (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; Wakker, Timmermans, & Machielse, 2003) to model how prehistoric people may have maximized their energy consumption and expenditure given assumptions about their diet known from the archaeological record. Through this it would be possible to model a variety of outcomes including the nature of catchments from known sites, dietary preferences and sustainable populations, the evolution from land-based to maritime diets in the region, seasonal resource stability, and even complex concepts such as resource competition and social dominance. Additionally, the approach could be used to generate an archaeological predictive model for sites, based on their likely function, in non-surveyed areas.

The overall model is designed as an intersection of a series of environmental and habitat models developed in the GIS. These are weighted-additive predictive models, exactly like the kind used for predicting archaeological site locations in other situations described above. But, these are intended to predict the habitat suitability for one specific resource at one specific time of year based on regional biological studies of that particular organism and existing local, state, and regional habitat models. Fifteen different environmental variables are used to develop geospatial models for 37 different forage categories (i.e. faunal or floral species or groupings), for each month of the year. These models represent suitability as a range of values from 0 (not suitable) to 1 (highest suitability) (Figures 13.1 and 13.2).

The habitat models are then converted to calorific surfaces based on estimates of species population size, density, reproductive rates, mortality, and resilience, during each month. A calorific surface is a GIS layer, which shows a prediction for the number of calories (kCal) one might acquire from any one pixel (or map unit) from each resource at any given time of year. Instead of a decimal value between 0 and 1, as in the habitat models, the calorific surfaces represent numbers of calories. By adding them all together, one gets a total number of predicted calories at every GIS pixel in the study area. The resulting 'available' calorific surfaces are then modified into models of 'returned' calories by subtracting the calorific 'costs' of acquiring the 'available' resources (Figures 13.3 and 13.4).

The cost formulas are based on energy expenditures for individuals and families calculated by Thomas (2008), for each of the resources used in the study. But, they are also tempered by known archaeological faunal/floral assemblages and the periodic introduction of different technologies; such as the bow-and-arrow, the introduction of crop staples, and grain storage. Subtracting calories based on rates of energy loss through decay and trade, as well as dietary preferences (e.g. personal tastes) leads to the outcome of a 'selected' energy model. In short, the available calories are the ones predicted by the habitat models. The returned calories are the predicted calories but with the costs of accessing and processing them subtracted. The selected calories are the ones remaining after some have been lost over time from decay, traded away to someone else, or left uncollected for some other reason.

Ultimately, the objectives of the model were meant to be explanatory, in that they helped answer questions about periods of site occupation, seasonality, diet sufficiency, patterns of exploitation, regional trade, and competition. To do so meant applying the locations of some 7000 known archaeological sites, but of which only 103 were well-dated domestic sites, to the analysis. Although no predictive model was actually intended from the outcome, Whitley used a sample area with a total of 308 known archaeological sites, did a simple unweighted combination of all calorific variables, and split them into three equal parts creating areas of low, moderate, and high total calorific value. These were then overlaid with the known archaeological sites and compared to see how many occurred in high probability areas.

This simple analysis showed that even without formal constructs separating out sites by period, function, or seasonality, or a more sophisticated evaluation of the boundaries between high and low potentiality, the gain values were in excess of 0.80; higher than typical data-driven models and unheard of for areas without high terrain dissection or limitations on water availability. The objective here was not to evaluate the application of this particular simplistic predictive model for development purposes, but to illustrate that a theory-driven approach was far more powerful than a data-driven one in predicting how human behaviour shapes site selection. The gain statistic, even with its inherent flaws, was merely used here as

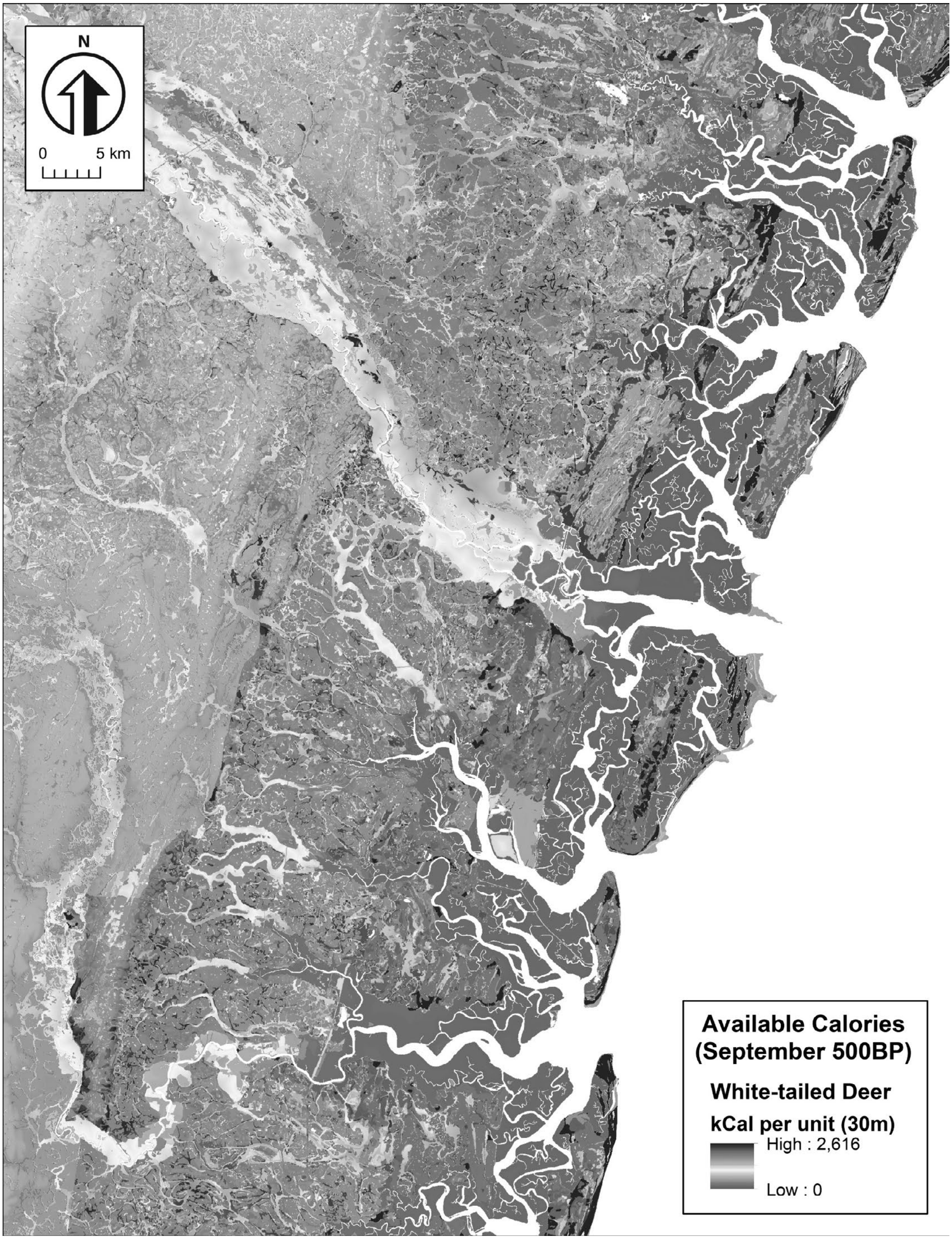

FIGURE 13.1 Southern portion of the coastal Georgia study area: maximum available calories for white-tailed deer (*Odocoileus virginianus*) for the month of September (ca. 500 BP). A colour version of this figure can be found in the plates section.

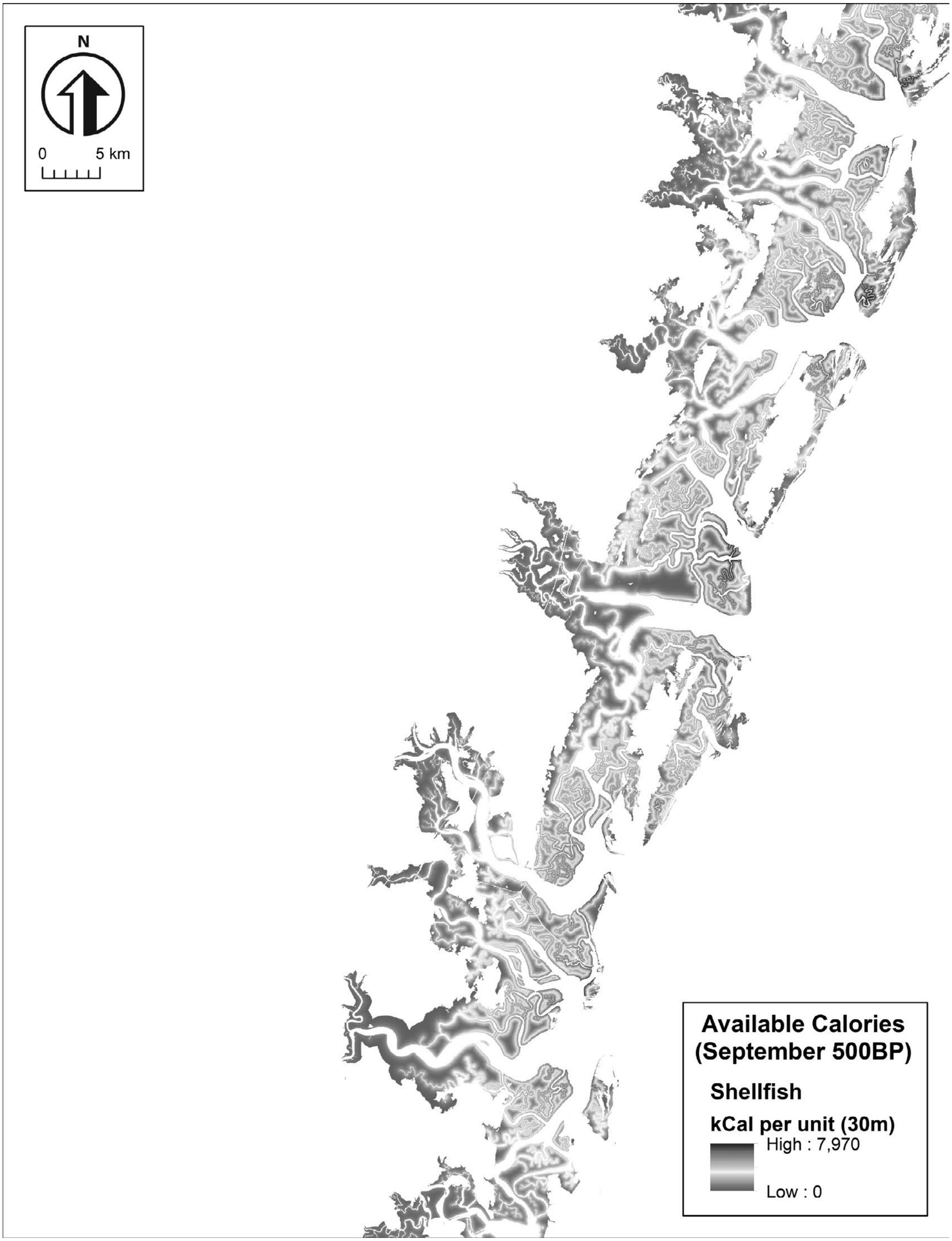

FIGURE 13.2 Southern portion of the coastal Georgia study area: maximum available calories for all shellfish species for the month of September (ca. 500 BP). A colour version of this figure can be found in the plates section.

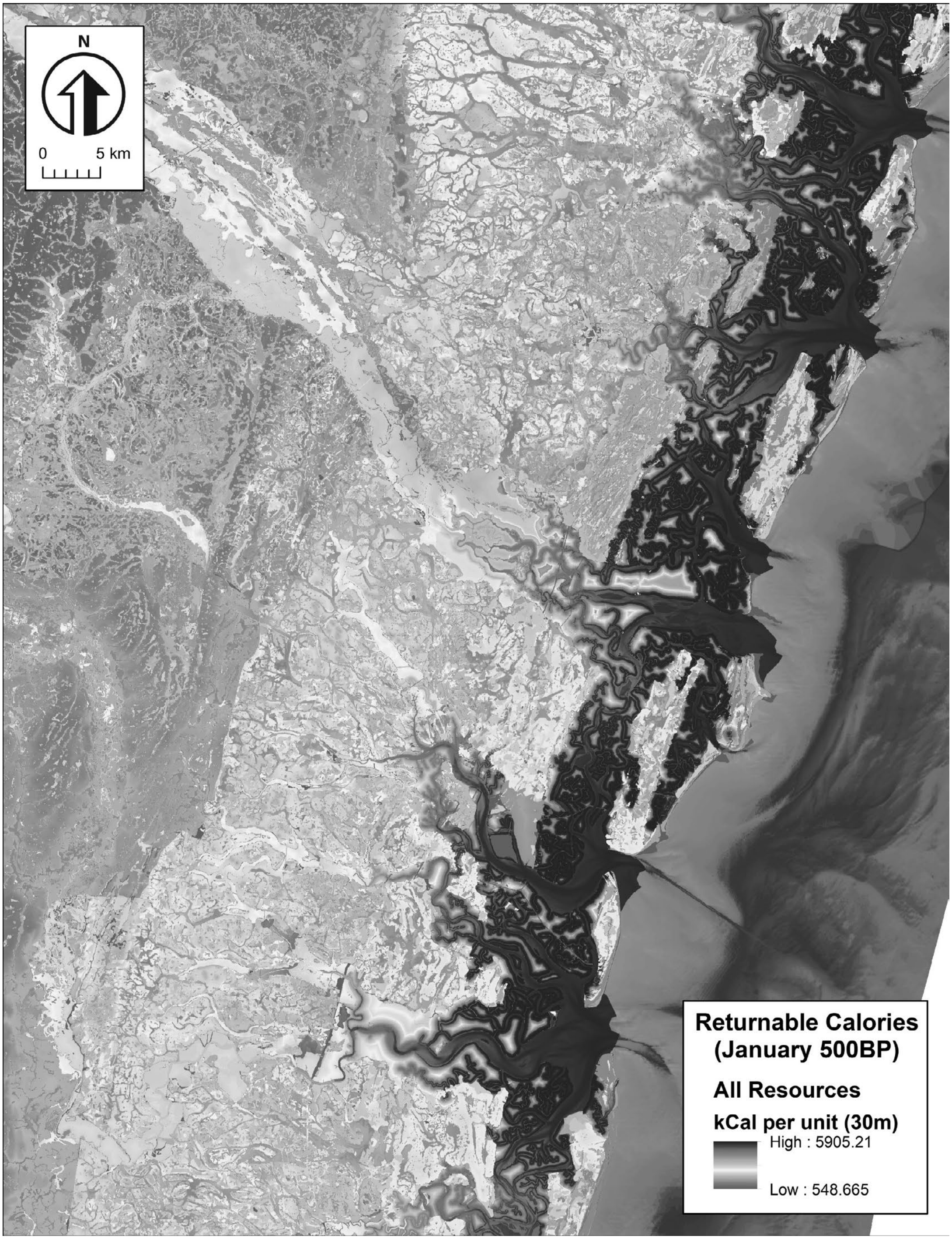

FIGURE 13.3 Southern portion of the coastal Georgia study area: returnable calories for all resources combined for the month of January (ca. 500 BP). A colour version of this figure can be found in the plates section.

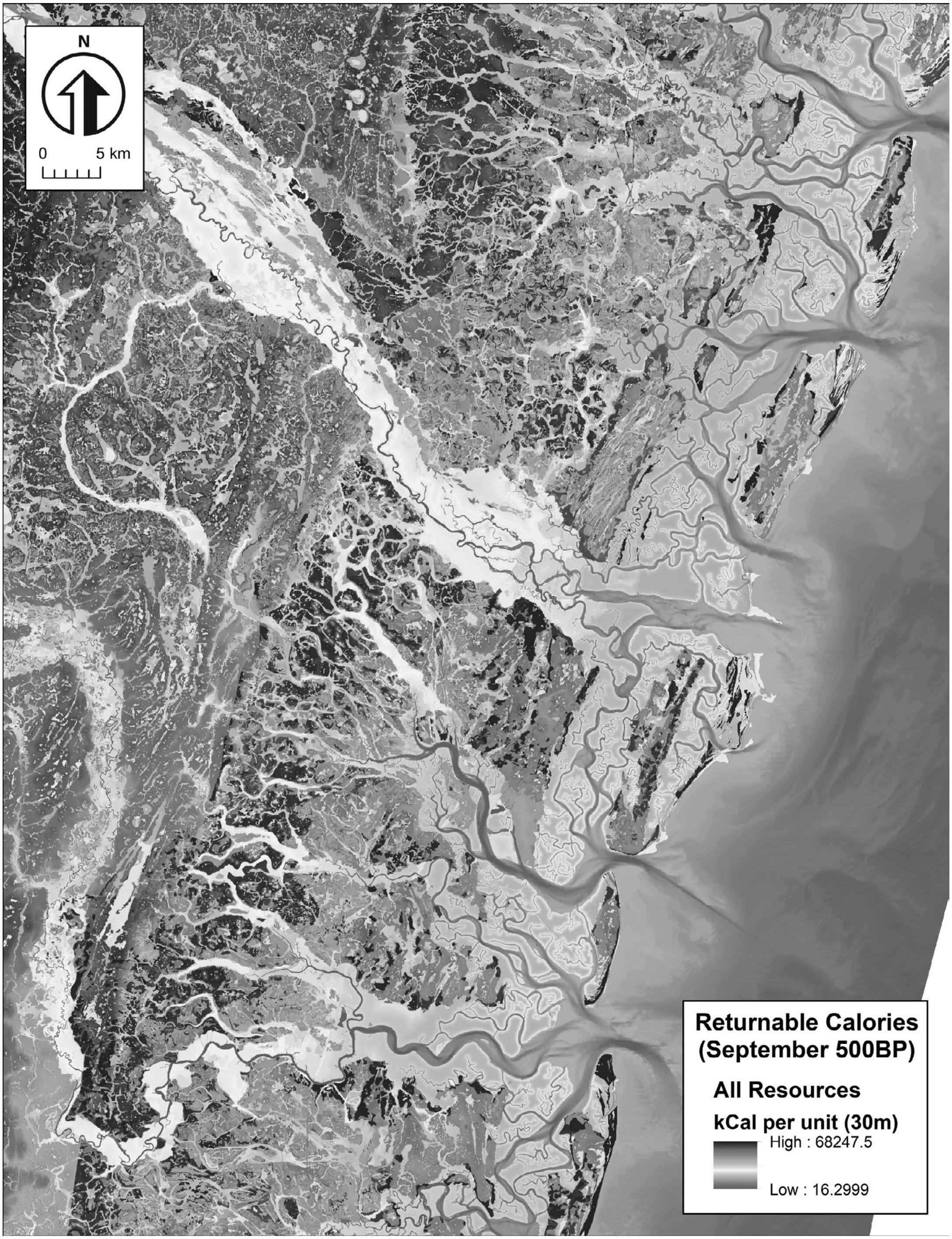

FIGURE 13.4 Southern portion of the coastal Georgia study area: returnable calories for all resources combined for the month of September (ca. 500 BP). A colour version of this figure can be found in the plates section.

a comparative device with far more expensive data-driven models like the Mn/Model. This approach was also used in a more formal predictive model successfully applied in parts of Louisiana, Arkansas and Mississippi (Whitley et al., 2011), but which remained untested in the field since federal funding expired.

The effects of pre-existing settlement on location choice

The predictive modelling examples given so far have only employed the environmental characteristics of site location. This set of predictors can be supplemented by analysing the spatial relationships between settlements. However, modelling the spatial influence of existing settlement on new settlement location choice was until recently mostly based on relatively simple theories about the effects of cost-distance. Archaeological studies in the 1970s, for example, already applied gravity models to infer networks within (political) territories, departing from the assumption that central places have a cluster of dependent sites surrounding them. Central places can be given weights to reflect different hierarchical ranks, and dependent sites are then connected to the central place which is closest in terms of weighted (cost-)distance (e.g. Hodder, 1974; Alden, 1979; Renfrew & Level, 1979; Ducke & Kroefges, 2008). These predicted territorial networks can also be used to infer the location of 'missing' sites in areas where connections are modelled but no settlements have been recorded.

It is only recently that researchers have started to explore more complex models of settlement interaction, and translate these into spatial predictions. Verhagen, Nuninger, Bertoncello, and Castrorao Barba (2016), for example, defined the concept of 'memory of landscape' on the assumption that not just the presence of current, but also of previously existing settlement may influence the choice of site location. Their case study for rural settlements from the Roman period in the south of France demonstrated that this effect existed, even when it did not seem to be a very strong predictor for this particular study area. The effect also changed depending on the timeframe considered. In some periods, new settlements seemed to be more pioneering, preferring locations in previously unexploited areas, whereas others showed 'opportunistic' behaviour by choosing locations close to previously settled areas. This approach was further elaborated by Nüsslein, Nuninger, and Verhagen (in press) in a case study in northeast France, where the creation and persistence of settlement patterns was observed to depend on the structure of local, hierarchical networks.

Rihll and Wilson (1987, 1991) modelled the presence of highly dominant sites without making initial assumptions about their importance on the basis of size or other considerations. Instead, they departed from equally weighted sites so that the weights were adapted in an iterative procedure depending on the number and strength of the connections for each site. A site that occupies a central position in the first iteration (when no weights are given) will receive a higher weight in the next one, and so on, until the network stabilizes. This has the effect of prioritizing centrally located sites and creates a strong hierarchical structure of nodes with a limited number of very important sites or 'terminals'. Bevan and Wilson (2013) demonstrated that creating connections between settlements from the Bronze Age on Crete on the basis of cost-distances in this way quickly imposes a 'hierarchy of activity' on the landscape, favouring specific connections for interactions. The effect is self-reinforcing, leading to a system of highly hierarchized settlement with only a few major arteries of movement, that broadly corresponds to the archaeological evidence. The model results however remain tentative and can better be seen as offering new interpretations of settlement structure than as reliable predictions of ancient networks of social and economic interaction. This approach has recently been applied in various other case studies (Rivers, Knappett, & Evans, 2013; Davies et al., 2014; Paliou & Bevan, 2016).

The influence of pre-existing settlement patterns on the development of a subsequent settlement pattern is not easy to assess, since it needs archaeological datasets with a high chronological and spatial resolution. In the absence of this information, we therefore can only model spatio-temporal patterns by including uncertainty. Bevan and Wilson (2013) and Paliou and Bevan (2016) assessed the quality of their models by including simulated additional settlements in the modelled network, based on a prediction of suitable site locations. By repeating this procedure a large number of times, it could be established whether the resulting networks' characteristics were stable or not. In this exercise, conventional predictive modelling was therefore used to support archaeological analysis, rather than the other way around.

Conclusion

Predictive modelling has a long and controversial history in archaeology. There are almost as many methods of creating a predictive model as there are actual models out there. Yet we routinely see new models that rely on a data-driven, correlative approach. These are almost always logistic regression-based analyses applied to strictly environmental parameters taken straight from the Judge and Sebastian (1988) playbook. Such techniques have worked well in some situations, but they leave a great deal to be desired from an explanatory perspective and are routinely criticized for their perceived environmental determinism, along with many other issues. Repeated application of these methods, developed in the 1970s and 1980s, seems to have driven a philosophical wedge between academic and CRM opinions regarding the value of predictive models (Verhagen & Whitley, 2012). Although there are new and innovative developments arising every year in archaeological predictive modelling, the general (incorrect) perception is one of methodological stagnation and theoretical limitations. Changing such a perception will eventually require new publications that can revisit the theory and methods of predictive modelling, and can put them into a more modern context.

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