A house with a view? Multi-model inference, visibility fields, and point process analysis of a Bronze Age settlement on Leskernick Hill (Cornwall, UK)☆

Stuart J. Eve[*], Enrico R. Crema [1]

UCL Institute of Archaeology, 31-34 Gordon Square, London WC1H 0PY, UK

ABSTRACT

This paper combines point-process modelling, visibility analysis and an information criteria approach to infer the reasons behind the Bronze Age settlement pattern of Leskernick Hill in Cornwall, UK. We formalise three alternative hypotheses as point process models characterised by different combinations of covariates. In addition to using traditional topographic variables, we use a form of affordance view-sheds, which we refer to as *visibility fields*, to investigate the visual properties of different parts of the landscape, both cultural and natural. We compare these three models by means of information criteria, and generate a fourth hybrid model by recombining variables drawn from each. The results reveal that a mixture of covariates drawn from the three hypotheses combined with a spatial interaction model provides the best overall model for the settlement pattern. We show that the settlement on Leskernick Hill was most likely the result of two separate decision-making processes, one to optimise the visibility of ritual monuments and important natural landmarks, and the other to optimise the visibility of nearby tin-extraction areas. We conclude that by using an information criterion approach it is possible to easily compare the models and identify which among these is the most satisfying in the present state of our knowledge.

1. Introduction

Locational models have a long tradition in archaeology. Regardless of their theoretical predispositions, archaeologists have always asked the simple question as to why an individual or group of individuals decided to live in a given place instead of another. However, there are often disagreements about the underlying processes and the key variables, and strikingly dissimilar hypotheses are proposed about how an observed pattern came into existence. Thus a fervent GIS practitioner might point to a set of topographic variables derived from a digital elevation model, advocating — implicitly or explicitly — the driving role of universal physiological principles. Another scholar might suggest an alternative set of drivers, placing greater emphasis on phenomenological aspects, such as the visibility of a key landmark in the landscape. These ideas have often been made artificially separate by conflicting research agendas and theoretical standpoints, and alternative models have rarely been considered together within the same analytical framework.

The practice of testing hypotheses and citing *p-values*, with the latter defined as the probability of obtaining the observed data given a null model, is undoubtedly the most common statistical workflow adopted by archaeologists. However, obtaining a *p-value* smaller than an arbitrarily defined threshold, and "successfully" rejecting a null-hypothesis does not always determine whether a given alternative hypothesis is better than another. Testing null-hypotheses should set the grounds for developing more interesting models, rather than being the final goal of a research endeavour. On the other hand, other archaeologists express a profound disbelief in the use of statistical methods for testing ideas concerning human cognition and phenomenological experience (e.g. Thomas, 2004). Nonetheless, a few exceptions (see Lake and Woodman, 2003; Frieman and Gillings, 2007) have proven that the development of bespoke methods can provide solutions to some of these problems, enabling the possibility of using statistical inference to answer phenomenological questions.

We consider the isolation between different bodies of archaeological theories as a profound limitation, and advocate a research framework where alternative models can be compared via a common and broader theoretical basis. In particular, we suggest that the suite of techniques related to statistical point-process models (PPM; Illian et al., 2008) and an information-criterion approach (Burnham and Anderson, 2002) can provide a robust solution to this problem.

Point process models offer a set of statistical tools for measuring and fitting both *induced* and *inherent* forms of spatial dependence (Fortin and Dale, 2005; see Bevan et al., 2013 for archaeological discussions). The former can be defined as the quantifiable effect of any external covariate to the intensity of a given point process, while the latter refers to the interaction between the points themselves in the form of attraction and/or repulsion at multiple spatial scales. Information-criterion and multi-model inference provides instead an alternative to the traditional hypothesis-testing approach. Its fundamental aim is to not to reject any hypothesis, but to rank models based on their likelihood, and penalising those that are more complex even if they seem to fit well, on the assumption that simpler is better (an assumption of parsimony). As a result, alternative models can be directly compared to each other in a quantitative fashion, or new models can be generated iteratively by recombining different variables.

The paper will be structured as follows. Section 2 provides background for the case study of Leskernick Hill and its Bronze Age settlement. Section 3 describes the dataset, while Section 4 will offer a detailed description of the statistical and computational methods. Section 5 illustrates and discusses our results, before we finally set out our main conclusions in Section 6.

2. Background

Leskernick Hill is situated in the north-eastern part of Bodmin Moor in Cornwall, UK (Fig. 1). It is an unimposing hill, dwarfed, over-looked and virtually enclosed by a ring of surrounding hills
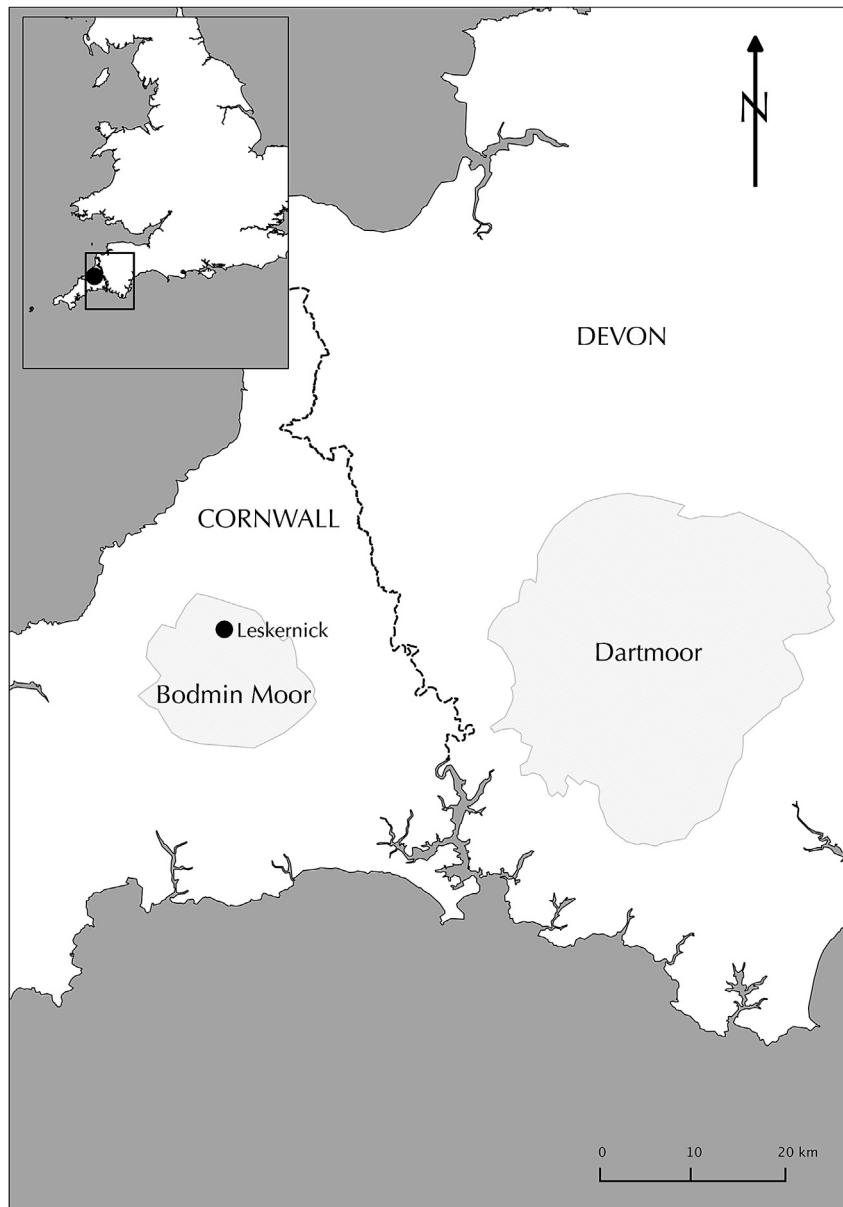

Fig. 1. General site location.

(Bender et al., 2007: 32; Fig. 2). Leskernick is typical of the rest of Bodmin Moor, situated on a huge lump or boss of various types of granite emerging from the Devonian and Carboniferous age sedimentary rocks. The granites have eroded, creating rocky tors and the acidic soils that form the basis of the moorland landscape (Rowe, 2005: 16). A striking feature of the moor is the lack of trees; no doubt exacerbated by both the blustery winds that continually harry the landscape and modern grazing practices. According to environmental evidence (Brown,1977; Caseldine, 1980; Walker and Austin, 1985), throughout the prehistoric past, "trees were substantially confined to the more sheltered valleys with the rest of the landscape being dominated by grassland and heath as today" (Tilley, 1996: 163). This view has subsequently been challenged, with more recent pollen analysis suggesting that the landscape was certainly more forested, especially during and prior to the Neolithic (Chapman and Gearey, 2000). The moor is criss-crossed by slow-moving, meandering streams, which run off the granite outcrops and into the marshy areas associated with the softer geology. Leskernick Hill itself sits within the shadow of the highest hill on Bodmin Moor, Brown Willy, whose peak is 420 m Above Ordnance Datum (AOD).

Throughout the 1980s and early 1990s a systematic survey was undertaken of all available aerial photographs of Bodmin Moor, along with targeted ground-truthing. Features in 193 km squares were plotted from aerial photographs and surveyed from the ground at scales of 1:2500 and in some places at 1:1000 (Johnson and Rose, 1994: xiii). The result was a gazetteer of all of the archaeological features visible on the ground from the early prehistoric through to the Post-Medieval period. The settlement on Leskernick Hill itself was excavated in the late 1990s by a team of archaeologists and anthropologists from University College

London. The first of two planned publications relating to the work, *Stone Worlds: Narrative and Reflexivity in Landscape Archaeology*, was published in 2007 to mixed reviews (Hicks, 2009; Barrett, 2009; Darvill, 2009). *Stone Worlds* is a brave attempt to present a reflexive approach to the archaeology of the Bronze Age, with specific reference to the settlement and surrounds of Leskernick Hill. Alongside traditional archaeological excavation, the team also explored the setting of house structures and the 'ritual' landscape by way of a number of new and often controversial techniques, including a phenomenological exploration of the settlement.

Archaeological evidence from the Leskernick Hill area begins in earnest in the Neolithic and Early Bronze Age (c. 3500–2300 BC) with the construction of various different types of monument, including a large multiple-kerbed cairn, a stone row running for c. 320 m ENE–WSW, and two stone circles (Fig. 3). Using a combination of C14 dating and stratigraphic analysis, Bender, Hamilton and Tilley suggest that only once the ritual elements of the landscape were in place, did settlement on the Hill occur. "Indeed, they probably settled at Leskernick precisely because these ritual places already existed or, rather, because the presence of these ritual places indicated that Leskernick Hill was an ancestral place of great and deep significance" (Bender et al., 2007: 82). The settlements, consisting of a mixture of house circles and enclosure walls, are located in two distinct areas, one on the southern side of the hill and one on the western.

There are a number of possible reasons for the Bronze Age settlement on Leskernick Hill. Bender and associates present a general argument that the Hill was settled as a traditional upland transhumance settlement, although they remain undecided as to whether it was occupied throughout the whole year or not. It is unclear which side of the hill was settled first, although the earliest
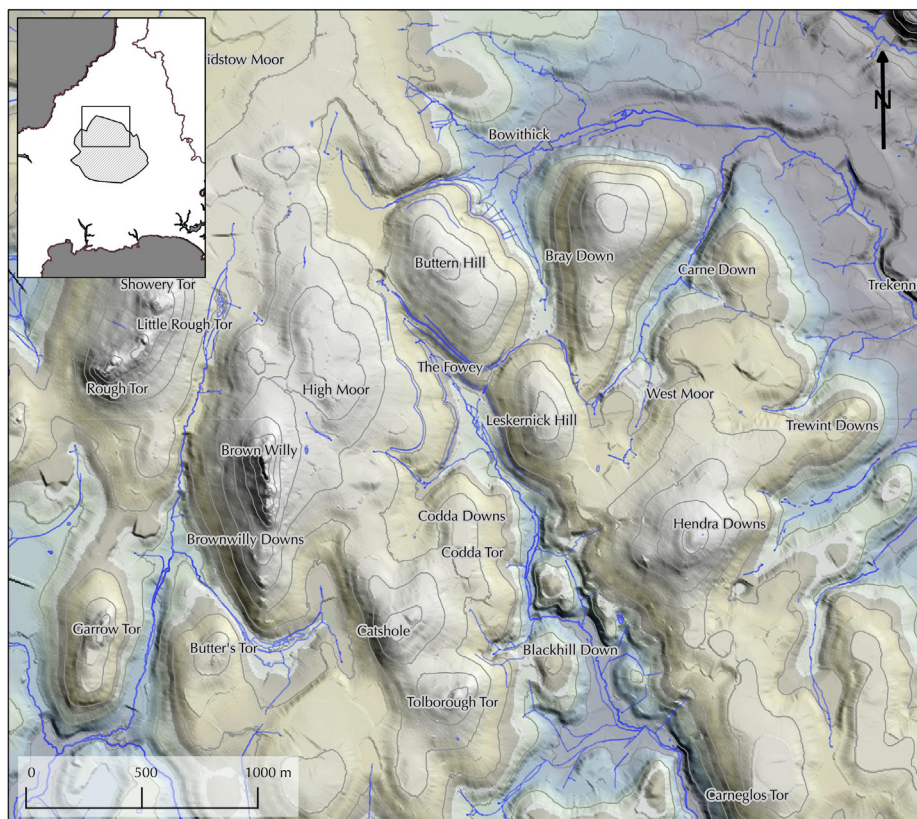
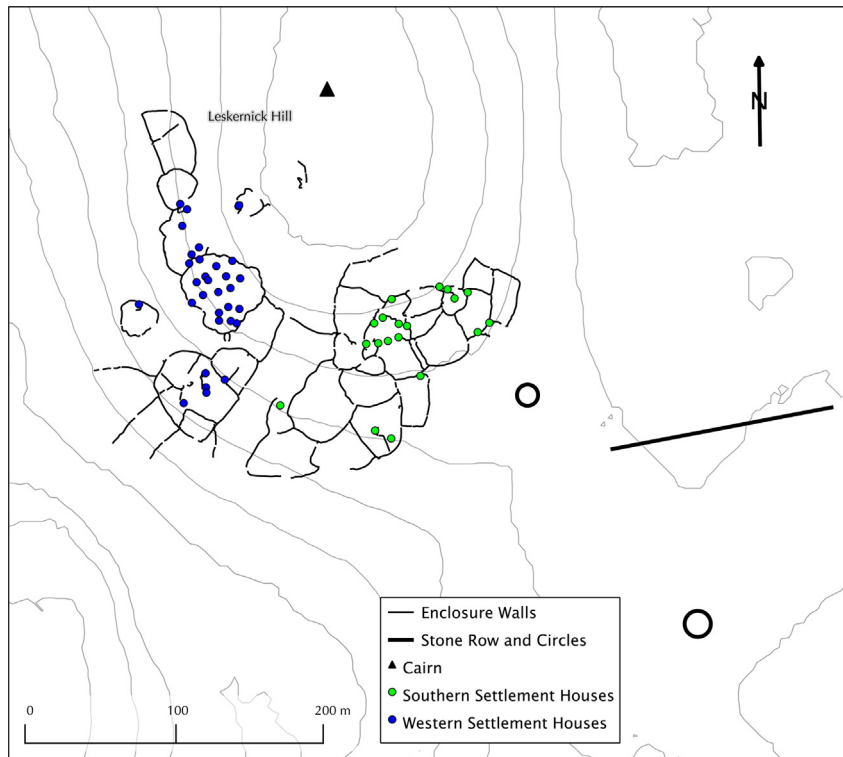

Fig. 2. Detailed site location.

Fig. 3. Leskernick Hill, showing house distribution and the ritual monuments.

radiocarbon date (1430–1265 cal BC) comes from the southern settlement. Peter Herring suggests that the enclosures and settlement on the southern side of the hill were established after the stone circles, as they are arranged in a respectful arc – "as if the fields, the secular creations on the hill, should not encroach too far onto an area used more for ritual or ceremony" (1997: 179). Bender et al. agree with this view, asserting that there was likely a small time-lapse between the creation of the ritual landscape and the more domestic settling of the hill.

This reserved view of the ritual area associated with the southern settlement is an important consideration in the settling of the Hill, indeed the central thrust of *Stone Worlds* concentrates on linking the settlement with the ritual aspects of the landscape both natural and cultural: as the authors suggest, "…the land is regarded as an ancestral creation and striking 'natural' features be they mountain peaks, unusual rocks, caves, springs, lakes, rivers, bogs, or large trees are sacred places" (2007: 81). The surrounding hills of Brown Willy and Roughtor feature heavily in Bender et al.'s interpretation, who put great importance on the views from the settlement to the cairns on their peaks.

An element of the landscape that is not discussed in any great detail by Bender et al. is the vast tin resource within the Leskernick Hill area. The areas around Leskernick Hill have been heavily exploited in the past for both eluvial and alluvial tinning, the locations of which have been recorded by the English Heritage survey (Herring et al., 2008, Fig. 4). Cornish tin was a highly prized mineral resource throughout the European Bronze Age (Penhallurick, 1986: 148), and although there is little direct evidence for prehistoric tin-working on the site of Leskernick Hill, a stone hammer, possibly used for grinding ore, was recovered from one of the cairns on Buttern Hill nearby (Cornwall Historic Environment Record Number 3506.70), and a Bronze Age spearhead was found in the tin-working below the Jamaica Inn at Bolventor (thirty minutes walk south from Leskernick Hill) (Penhallurick, 1986: 207). During

excavations of the settlement itself circumstantial evidence of quartz chips were discovered, that may be a "by-product of the damage sustained by quartz pounders when used to smash something hard such as cassiterite [tinstone]" (Bender et al., 2007: 122). This lack of direct evidence could be the result of a number of factors. First, the excavations undertaken at Leskernick were relatively limited; therefore evidence might not have been discovered in the specific areas of excavation. Second, the majority of Bronze Age artefacts relating to tin working are found on the tin grounds themselves. Most of the tin ground in Cornwall was also exploited during the late medieval and post-medieval period, and if Bronze Age (or indeed later) artefacts were recovered in the process, they were quite often taken as souvenirs by the tinners, or even thrown into the smelt along with the other recovered tin (Penhallurick, 1986: 173). Presumably much of the evidence was never reported or the artefacts were lost. The spearhead from Bolventor is clear evidence that they reached the tin ground nearby in the Bronze Age. Weighing up the circumstantial evidence it seems extremely unlikely that the inhabitants of Leskernick were living on one of the major sources of tin in the ancient world without knowing about it or without extracting it. It is more likely that the inhabitants of Leskernick settled on the spot precisely because the tin was there. If this is the case, it follows that they may have placed their houses in areas with access to the tin streams and probably in areas with good views of the tin extraction grounds.

This does not explain the presence of the earlier ritual monuments, indeed "…no good correlation has yet been made between Bronze Age mines and the distribution of Bronze Age monuments" (Timberlake, 2001: 189–190). It may be that they originally settled because of the ritual monuments and the quality of the grazing area, and the tin deposits were discovered at a later time, causing an increase in the size of the settlement area and the building of the houses in the western area. As Timberlake suggests, "… the process of prospection may well have been a subsidiary activity of
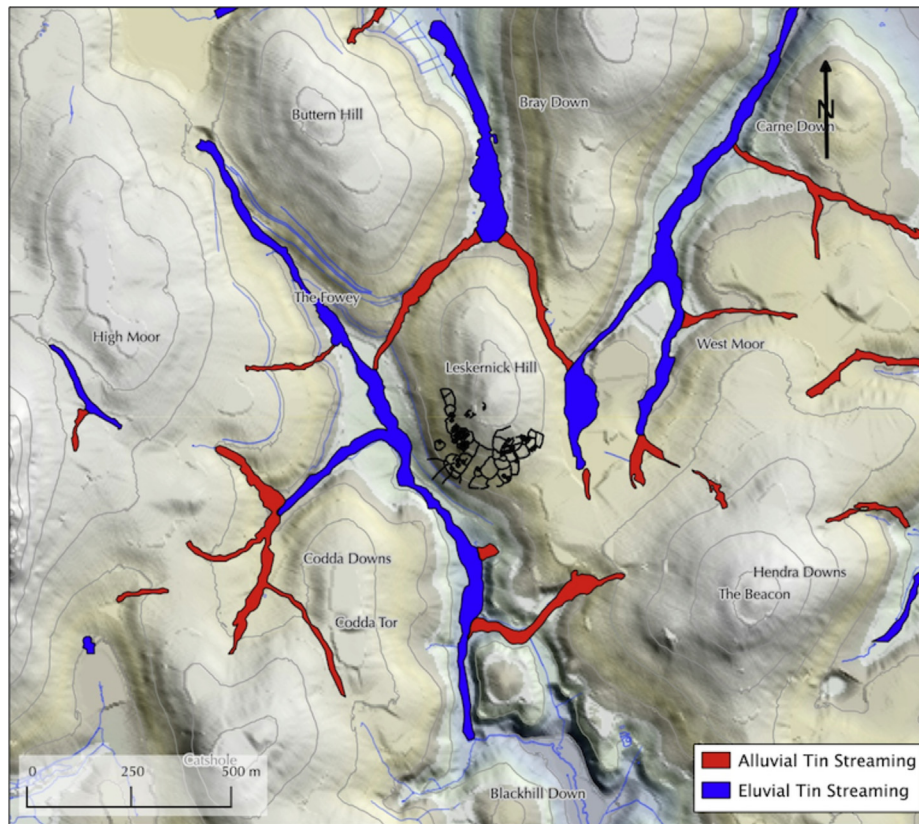
Fig. 4. Areas of tin streaming (after Herring et al., 2008).

transhumance agriculture, and may thus have been linked with the role of pastoralists in the uplands" (2001: 184), which could explain the two distinct areas of settlement: the western houses may have been built once the tin was discovered or was being exploited to a greater extent, and the inhabitants wanted to maintain some form of visual contact with the extraction area.

We are left then with two distinct models for the placement of the houses in the settlement of Leskernick Hill, as a function of why Leskernick was settled in the first instance.

1. If the area was settled due to the existence of the ritual land-scape, then the houses would be placed to maintain a visual relationship with Brown Willy, Roughtor and the ritual monu-ments in the area near the southern settlement (**model A**).
2. If the area was settled due to the existence of the tin deposits, then the houses would be placed in locations with a stronger visibility of the areas possibly dedicated to tin extraction (allu-vial and eluvial valleys; **model B**).

If we ignore the primary motive of why Leskernick was chosen out of a wider set of hills on Bodmin Moor, we might add a third simple functionalist hypothesis:

3. The houses were placed in the lee of the prevailing wind (the southern side of the Hill is ideal for this), to be at a certain elevation so as not be flooded easily and to be in an area of flatter overall ground (**model C**).

3. Data collection

The data we used for the analysis below has been collected and derived from a number of different sources. Unfortunately the

majority of this area of Bodmin Moor has not been subject to the Environment Agency's programme of LiDAR survey, therefore the best resolution continuous Digital Terrain Model (DTM) available was the Ordnance Survey's Landform PROFILE product which is digitised from contours at 1:10,000 resulting in a digital DTM with a horizontal pixel resolution of 10 m and vertical accuracy of ±2.5 m (OS, 2013). The majority of the archaeological data layers were kindly supplied by the Cornwall & Scilly Historic Environment Re-cord. Other archaeological features (including the location of some of the monuments) were digitised directly from information sup-plied in Johnson and Rose (1994) and Herring et al. (2008). The tin-streaming areas were also digitised from the information in Herring et al. (2008): while there is no direct evidence that these areas were exploited in the Bronze Age, they do indicate areas of possible tin extraction, and have been used as a proxy for areas that could have been exploited.

4. Method and theory

4.1. Point process models and information criterion

Point pattern analysis (PPA) — a subset of spatial analysis where the basic units can be abstracted as dimensionless points — has a long-lasting tradition in archaeology going back to the early works by Dacey (1973) and Whallon (1974), and has recently been reinvigorated by the wider availability of simulation-based tech-niques requiring computationally intensive workflows. The flexi-bility of these methods facilitated its adoption in a variety of contexts, from intra-site spatial analysis (Orton, 2004; Vanzetti et al., 2010) to the surface scatters retrieved from intensive sur-veys (Bevan and Conolly, 2013; Crema and Bianchi, 2013; Markofsky, 2014), the meso-scale distribution of residential units (Crema et al., 2010), and the regional distribution of

settlements (Bevan and Connolly, 2006; Mayer, 2006; Palmisano, 2013). In the great majority of these studies, PPA offers a statistical tool to establish whether an observed distribution deviates significantly from the null hypothesis of a random pattern. This is undoubtedly a useful exercise, as PPA allows us to statistically establish instances of clustering and dispersion as alternative hypotheses to a random spatial pattern observed at different spatial scales.

However, recent developments in statistical science are now offering the necessary framework for building more explicit models than this, where the relationship between external covariates and the point process (i.e. induced spatial dependency or first order properties; Bailey and Gatrell, 1995; Fortin and Dale, 2005), as well as internal forces of reciprocal attraction and repulsion (i.e. inherent spatial dependency or second order properties; Bailey and Gatrell, 1995; Fortin and Dale, 2005) can be simultaneously modelled (Baddeley and Turner, 2000; Illian et al., 2008). The few examples where these point process models (PPM) have been applied in archaeology have been successful. For example, Bevan and Wilson (2013) used PPM to simulate missing settlement locations for their network analysis of settlement hierarchy in Bronze Age Crete, while Vanzetti et al. (2010) examined the distribution of artefacts to support their hypothesis that the "Ice-man" was a burial.

The most intriguing, yet unexplored, aspect of these PPMs is the possibility of formally comparing competing models through the use of an information criterion, a statistical measure of model quality. Details of the underpinning philosophical principles behind information criteria can be found in Burnham and Anderson's monograph (2002); here we illustrate the most relevant points for our research agenda. One of the fundamental assumptions of this body of statistical theories can be summarised by George E.P. Box's popular quote, "all models are wrong, but some are useful" (Box and Draper, 1987: 424). A "true model" is in this sense an oxymoron (Burnham and Anderson, 2002: 20), and its pursuit a meaningless exercise. Thus, scientific endeavour should focus on the generation and selection of *better* models; defined as approximations of reality. The key question then becomes the selection criteria, what helps us choose one model instead of another. The role of empirical data is undoubtedly pivotal; the best model amongst a set of candidates can be regarded as the one that is more likely to produce the observed record.

However, once we have multiple models we face the problem of dealing with different levels of complexity, and quite often candidates with a higher number of parameters produce higher likelihoods. This bias goes against the principle of parsimony, which dictates that unnecessary details should be removed (also known as "Occam's razor"). In the realm of multi-model selection, this principle is used to avoid instances of over-fitting, where, misguided by small idiosyncrasies, we integrate too many variables within our sample. This will generate a model that will be heavily biased by small anomalies, which are more likely to be random elements than genuine consequences of past decision-making. The best model is thus the one that provides the highest amount of information that we are interested in, with the lowest level of complexity and number of assumptions. This theoretical principle is integrated by "weighting" the likelihood of the model, favouring simpler models over complex ones. In practical terms, this implies that the addition of a parameter should be always justified by a *significant* improvement of the likelihood, as a small improvement is always expected.

Despite the suitability of information criteria for many types of archaeological research questions, its adoption in archaeology has been rare. The few exceptions, however, showed its ability to perform analysis when multiple contrasting hypotheses were compared with each other. For example, Beheim and Bell (2011) have examined whether the distribution of decorative and structural traits of Pacific Island canoes are best explained by ecological adaptation, cultural inheritance, or cultural interaction, while Manning et al. (2013) have analysed the variance in animal bone distribution, selecting from a set of candidate models that describe how animal exploitation strategies developed and/or spread in Neolithic Europe. These recent works illustrate how the problem of "equifinality" (i.e. multiple process generating similar patterns; Hodder and Orton, 1976; Premo, 2010) can be tackled from a different perspective. Alternative models can be compared to each other in a quantitative fashion, helping us to decide whether one model is better than the other, or whether two or more models are equally "close" to reality.

Analysing the residential units of Leskernick Hill by testing its spatial distribution against the null hypothesis of a random pattern is not sufficient for answering our archaeological question. The rejection of the null hypothesis does not require sophisticated statistical techniques in this case (a visual inspection can easily tell us that the points are clustered on the southern slopes of Leskernick, see Fig. 3) and more importantly, does not help us in choosing between the alternative hypotheses for the placement of the settlement as proposed in Section 2. The clustering observed in Fig. 3 might be due to the existence of only a few places in the landscape that satisfied the settlers' priorities, and hence dwellings were "pushed" closer to each other. In such a case, we would like to determine, if we can, what the nature of these priorities were, and whether they conform to any of the proposed models. We also need to consider the alternative hypothesis of a strong inherent form of spatial dependency, where dwellings were "pulled" by the presence of other dwellings. Finally, we also need to consider the possibility of a mixture of "push" and "pull" forces.

We first built a series of PPMs with different combinations of covariates that formalise the hypotheses suggested in Section 2. This enabled us to choose which of the proposed models is more likely to generate the observed pattern, given the smallest number of assumptions. Subsequently we examined the possible effects of inherent spatial dependency by measuring the residuals of the models (Baddeley et al., 2012). The residuals in this case are significant deviations of the empirical record from the expectations dictated by our fitted models, more specifically instances where we observe higher or lower than expected density of houses at specific spatial scales. These residuals were then used as a guideline for choosing the most appropriate interaction model. Model fitting has been conducted using the *spatstat* package in R (Baddeley and Turner, 2005), while we chose Bayesian Information Criterion (BIC)[2] for comparing different models and choosing the best combination of variables for each (Schwarz, 1978).

4.2. Construction of the covariates and visibility fields
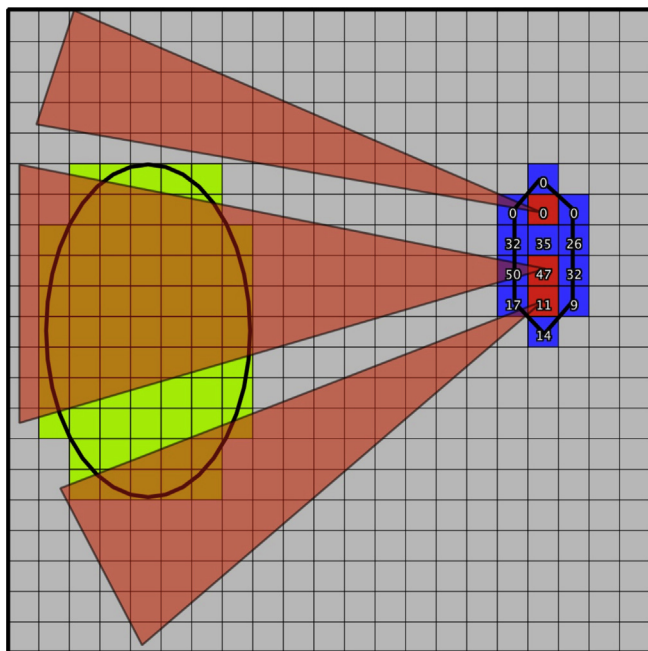
The basic topographic covariates were derived from the DTM: slope and aspect. To test the visibility from the settlement to the topographic features under study (Brown Willy, Roughtor, the alluvial and eluvial tin-streaming areas and the area of the ritual monuments) it was necessary to devise a new technique deriving

---

[2] The primary difference between BIC and the more commonly adopted Akaike Information Criterion (AIC) resides in the penalty function. This is $2p$ for AIC, and $ln(n)p$ for BIC, where p is the number of parameters (covariates) and n is the sample size. Thus, BIC will require more parsimony in the model if the sample size is large. From a practical perspective there the broad conclusions of our analysis were the same using BIC and AIC, and the few exceptions have been flagged (see below).

from standard viewshed analysis. Employing the method illustrated in Fig. 5, and using the GRASS GIS package *r.viewshed* with a batch script written in Python, a separate viewshed was created for every raster cell within the area of Leskernick Hill. Each cell on the Hill was then coded with the number of cells of each of the topographic features that coincided with its viewshed. This type of analysis was first used by Mark Gillings when looking at the amount of sea that could be observed from various positions on the island of Alderney (2009: 344–345). Gillings used what he terms 'affordance viewsheds' to suggest areas of Alderney that may have commanded expansive sea views, and hence may have been attractive for monument construction. In our case we used a similar methodology to create a *visibility field* for each of the visibility covariates as shown in Fig. 6.

4.3. Model formalisation

We first formalised our three competing hypotheses as instances of a point process known as inhomogeneous Poisson, where the intensity of the points process λ at any portion of the window of analysis is a function of a baseline frequency and the additional effects induced by external covariates (i.e. independent predictive variables). For each hypothesis (see Section 2) we chose a different set of "seed" covariates, from which we obtained a final selection through a stepwise selection (see below). The first model (**A**) assumed that the intensity of the point process varied as a function of the visibility of three key features of the landscape, Roughtor, Brown Willy, and the ritual area south of Leskernick. The second model (**B**) also assumed that visibility played a pivotal role, albeit this time the key features are the visibility of eluvial tin streaming areas, alluvial tin streaming areas, and both. As briefly discussed in Section 2, this choice is based on a working hypothesis that these locations might have been associated with the extraction of tin in the

Bronze Age. The third model (**C**) ignores visibility and instead looks at key topographic features of the landscape at Leskernick, namely elevation, slope, and aspect. Finally we defined a "basic" model (**Zero**) where the intensity of the process is homogeneous over space and independent to all covariates. This will be the equivalent to the baseline (the intercept) of regression models and has been created specifically to establish a comparative landmark.

5. Results

### 5.1. Poisson model building and comparison

For each of the three candidate models we first identified the best combination of parameters by automatically removing different combinations of covariates and choosing the permutation that minimised the BIC. The resulting inhomogeneous Poisson models have been then compared to each other using Information criterion weights (w), which provides a relative measure for each model (i.e. the total sum of all w yields 1). The results (Table 1) showed that when we consider the whole settlement as the result of the same behavioural process, **model A** gives the best performance ($w_A = 0.715$), followed by **model B** ($w_B = 0.285$). Separating the two clusters of dwellings provides a better insight of these values. In fact, when we consider only the southern settlement, **model A** offers the best performance ($w_A = 1$), and when we consider the western, **model B** has the highest weight ($w_B = 1$). This striking difference in the model comparison process clearly supports the initial insight that the two clusters of dwellings are likely the result of two contrasting processes of decision-making. While the low weights of the **model Zero** were predicted, the poor performance of **model C** was unexpected, and shows how topographic variables that are widely used in regional analysis, do not alone offer the best explanations in this case.

5.2. Identifying the best model

The selection process depicted in Table 1 clearly identifies the existence of the single best model for the southern and western clusters of dwellings. We did not consider the possibility that a hybrid model, where the covariates are drawn from each of the three models considered here, might better explain the observed pattern. We identified the best possible combination of covariates (**model D**) using the stepwise model selection procedure, taking, this time, all nine covariates used in this study as starting "seeds". Table 2 shows the covariates selected for the best model, while a comparison of the information criterion weights with the **models A, B**, and **C** is shown in Table 3. The results show the shared presence of two covariates in all models: visibility of Brown Willy and Elevation. It is worth remembering that the latter variable was part of **model C**, which gave the lowest BIC of the three models. This suggests that topographic variables can be excellent predictors if combined with covariates drawn from other sets of hypotheses.

The comparison of the BIC shows, as expected, the highest w for model D. This is by far the best model when we consider the whole settlement and the western cluster ($w_D = 1$ in both cases), but in the case of the southern cluster its only slightly better than **model A** ($w_D = 0.535$ and $w_A = 0.465$).[3] This suggest that the phenomenological hypothesis proposed by Bender et al. and Herring (the houses were placed for good views of the ritual areas) is still a good

Fig. 5. The creation of a visibility field. Individual viewsheds are calculated for every cell that falls within the visibility field (shown in blue). Each cell of the visibility field is then coded with the total number of the cells in the target area (green) that fall within its viewshed. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

---

[3] When using AIC the weights of the two models changed slightly, giving a slighter advantage of model D over model A ($w_D = 0.649$ and $w_A = 0.351$).
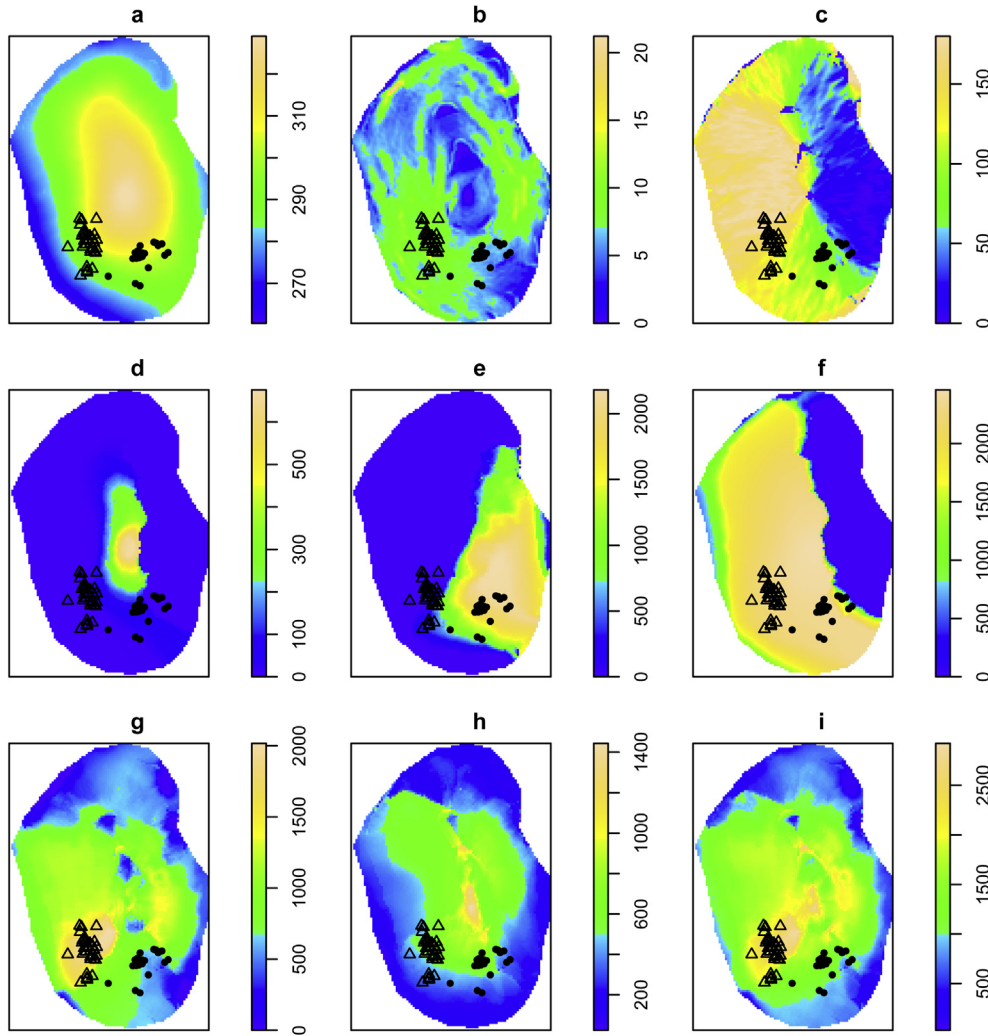
Fig. 6. Covariates used for PPM along with the western (hollow triangles) and southern (filled black circles) settlement: a) elevation (metres above sea level); b) slope (degrees); c) aspect (degrees from North); d) visibility of Roughtor; e) visibility of ritual area (stone circle); f) visibility of Brown Willy; g) visibility of eluvial valleys; h) visibility of alluvial valleys; i) combined visibility of alluvial and eluvial valleys. All enclosing rectangles are sized 920 × 1320 m.

Table 1
Poisson model selection.

Model name	Covariates	Delta BIC	df	Weights
Whole Settlement				
A	Brown Willy, Roughtor, Ritual Area	0	4	0.715
B	Eluvial	1.8	2	0.285
C	Elevation, Aspect, Slope	65.2	4	<0.001
Zero	–	74.3	1	<0.001
Southern Settlement				
A	Brown Willy, Roughtor, Ritual Area	0	4	1
C	Aspect	64.1	2	<0.001
B	Alluvial, Alluvial + Eluvial	65.8	3	<0.001
Zero	–	65.9	1	<0.001
Western Settlement				
B	Alluvial, Alluvial + Eluvial	0	3	1
A	Brown Willy, Roughtor, Ritual Area	29.3	4	<0.001
C	Elevation, Aspect, Slope	109.6	4	<0.001
Zero	–	144.7	1	<0.001

Table 2
Covariates for model D.

Covariate name	Estimate	S.E	Z-test	95% C.I lo	95% C.I hi
Whole Settlement:					
Intercept	−4.6602	5.9107	NA	−16.2450	6.9247
Elevation	−0.0505	0.0216	<0.05	−0.0928	−0.0082
Roughtor	−0.0184	0.0048	<0.0001	−0.0277	−0.0091
Ritual Area	0.0020	0.0003	<0.0001	0.0014	0.0026
Brown Willy	0.0023	0.0004	<0.0001	0.0014	0.0031
Alluvial + Eluvial	0.0029	0.0004	<0.0001	0.0022	0.0036
Southern Settlement:					
Intercept	8.3060	10.7972	NA	−12.8561	29.4681
Elevation	−0.1040	0.0437	<0.05	−0.1896	−0.0183
Slope	0.3937	0.1591	<0.05	0.0819	0.7056
Ritual	0.0043	0.0010	<0.0001	0.0024	0.0061
Brown Willy	0.0021	0.0005	<0.0001	0.0011	0.0031
Western Settlement:					
Intercept	−33.0267	11.2413	NA	−55.0593	−10.9941
Elevation	−0.2002	0.0703	<0.001	−0.3379	−0.0624
Aspect	0.0393	0.0188	<0.05	0.0025	0.0760
Roughtor	−0.0476	0.0193	<0.05	−0.0855	−0.0098
Brown Willy	0.0319	0.0096	<0.0001	0.0131	0.0507
Alluvial + Eluvial	0.0034	0.0006	<0.0001	0.0023	0.0044

Table 3
Poisson Model Selection with model Best.

Model name	Covariates	Delta BIC	df	Weights
Whole Settlement				
D	**Elevation**, Roughtor, Ritual Area, **Brown Willy**, Alluvial + Eluvial	0	6	1
A	Brown Willy, Roughtor, Ritual Area	71.1	4	<0.001
B	Eluvial	72.9	2	<0.001
C	Elevation, Aspect, Slope	136.3	4	<0.001
Zero	–	145.5	1	<0.001
Southern Settlement				
D	**Elevation**, Slope, Ritual Area, **Brown Willy**	0	5	0.535
A	Brown Willy, Roughtor, Ritual Area	0.3	4	0.465
C	Aspect	64.3	2	<0.001
B	Alluvial, Alluvial + Eluvial	66	3	<0.001
Zero	–	66.2	1	<0.001
Western Settlement				
D	**Elevation**, Aspect, Roughtor, **Brown Willy**, Alluvial + Eluvial	0	6	1
B	Alluvial, Alluvial + Eluvial	25.3	3	<0.001
A	Brown Willy, Roughtor, Ritual Area	54.5	4	<0.001
C	Elevation, Aspect, Slope	134.9	4	<0.001
Zero	–	170.0	1	<0.001

candidate model if we focus solely on the southern cluster of dwellings in Leskernick.

5.3. Interaction

We examined the goodness-of-fit of the three best models using the residual K function (Baddeley et al., 2012). The function allows us to determine the presence of aggregation and segregation that are not expected from the inhomogeneous Poisson models constructed above. Fig. 7 compares the observed residuals against ninety-nine simulated values and shows a good fit (the solid line of the observed data within the grey shaded confidence area) only for the southern cluster of dwellings (Fig. 7c). In contrast, the distribution of the southern dwellings shows significant levels of aggregation unexplained by model D at spatial scales from 30 to 160 m (Fig 7b). Similarly when we consider the entire settlement (Fig. 7a), the residual K function shows some levels of unexplained aggregation between 30 and 60 m.

The residual K function thus shows that the observed distribution of dwellings is characterised by a clustering generated by either a further unknown covariate, or by the presence of some form of interaction between the points themselves. We explored the latter hypothesis, by shifting from a Poisson point process to a Gibbs point process, which can formally integrate the spatial interaction between the dwellings (i.e. inherent spatial dependency). One of the most flexible model of point interaction is the area interaction point process (Baddeley and van Lieshout, 1995, see Bevan et al., 2013 for an archaeological application), which in its canonical scale-free form is defined by r, the range of spatial interaction process, and η, an interaction parameter equal to 1 for a random Poisson process, <1 for a repulsion process with a regular distribution of points, and >1 for a clustered process. In practical terms, η can be fitted from the data, while the choice of r can be guided through a maximum pseudo-likelihood approach.

Fig. 8 shows the profile of the maximum pseudo-likelihood (i.e. how the model likelihood varies as a function of different values assigned to r) and the resulting choice of r for the southern (Fig. 8a) and whole settlement data (Fig. 8b), along with the residual K function of the fitted Gibbs point process (Fig. 8c and d). Both new models show an improved fit to the empirical data, (compare with Fig. 7a and b) and their respective BIC shows a significantly smaller

value compared to the Poisson models discussed above (with both w equal to 1).

6. Conclusions

This paper quantitatively compared several alternative models of the generative process behind the settlement pattern observed on Leskernick Hill on Bodmin Moor. We can summarise the main conclusions of our work as follows:

- The southern and western clusters were likely to have been generated from different underlying processes and relationships with the surrounding landscape.
- The best models of the three candidates introduced in Section 2 (Table 1), are **model A** (visibility of ritual and key landmarks alone) for the whole settlement and the southern cluster, and **model B** (visual relationship with areas potentially related to tin extraction alone) for the western cluster. In all cases **model C** (local topographic features alone) performed poorly and was the lowest ranked after the null model of a complete spatial randomness.
- The best Poisson model for each of the three subsets of data (**model D**, Table 3), obtained from a stepwise variable selection, indicated that a mixture of covariates associated with different models provides the lowest BIC. Interestingly, the two variables that were selected in all three subsets (Table 2) were the visibility of Brown Willy (originally a covariate of **model A**) and elevation (originally a covariate of **model C**). The latter indicates how covariates that are included in poor models (**model C**, in this case akin to many environmentally deterministic models) might still be a strong predictor when combined with variables from other models.
- The absolute best inhomogenous Poisson model (**model D**) of the southern settlement was only slightly better than **model A**, indicating how the visibility of ritual areas and key landmarks alone is still of overriding importance, suggesting that Bender et al.'s original hypothesis should not be discarded.
- The residual K function analysis (Fig. 7) showed that the best Poisson model of the whole settlement and the western cluster indicated an unexplained presence of spatial attraction between residential units. A Gibbs point process model which integrated such forces provided a better model (lower BIC), suggesting that the observed patterns are not purely a result of induced spatial dependency, but possibly related to a decision-making process where dwellings were constructed purposely in proximity to each other.

In general, the formalisation of PPM and the model selection exercise have allowed us to set a comparative environment where novel hypotheses can be easily compared with existing ones. The relevance of **model B** for the western cluster, and the inclusion of the visibility of alluvial and eluvial tinning areas in the best model (**model D**) obtained from the stepwise selection of the available covariates, indicates that further investigation of the tin extraction activities at Leskernick is warranted. In retrospect, the relevance of mixed covariates in the highest ranked model is not surprising, and perhaps echoes the common view that, ultimately, both physical environment (**model C**) and socially constructed perception of past landscapes (**model A**) are crucial for understanding the archaeology of human settlement. Nonetheless, this truism is rarely supported by statistical analysis in formal terms, and we hope that our work has illustrated one possible way to tackle such a problem. It is paramount also to note that the choice of the window of analysis has undoubtedly reduced the explanatory power of certain variables at the expense of others. Our choice of Leskernick Hill as
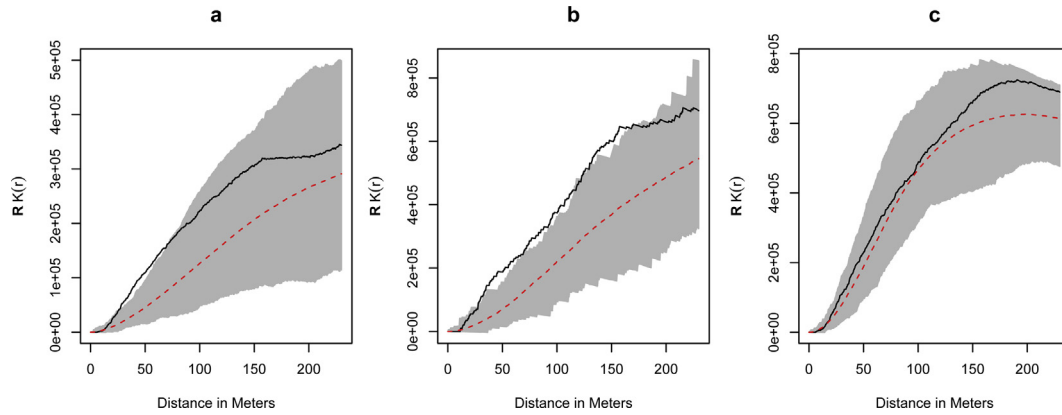
Fig. 7. Residual K functions of the inhomogenous Poisson model D for: a) the whole settlement; b) southern cluster; c) western cluster. The solid lines show the empirical residual K function, while the grey shaded area has been generated from 99 simulations of the point process, with the red dashed line showing the mean expectation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

window effectively determined the creation of models that ignore the underlying processes that led its inhabitants to settle there instead of on another hill. Instead, we focused on why individual houses where constructed on specific places on the hill instead of others.

The formalism of PPM and the generation of *visibility fields* based on computationally intensive GIS-analysis provided the structure for implementing an information criterion based model selection. The adoption of the latter has some key epistemological attractiveness for research questions similar to the one proposed here. The purpose of a model selection exercise is not to determine what was the truth, but to establish which model, among those proposed, is the *closest* to the truth. This does not necessarily guarantee the presence of a single best model, as we have observed
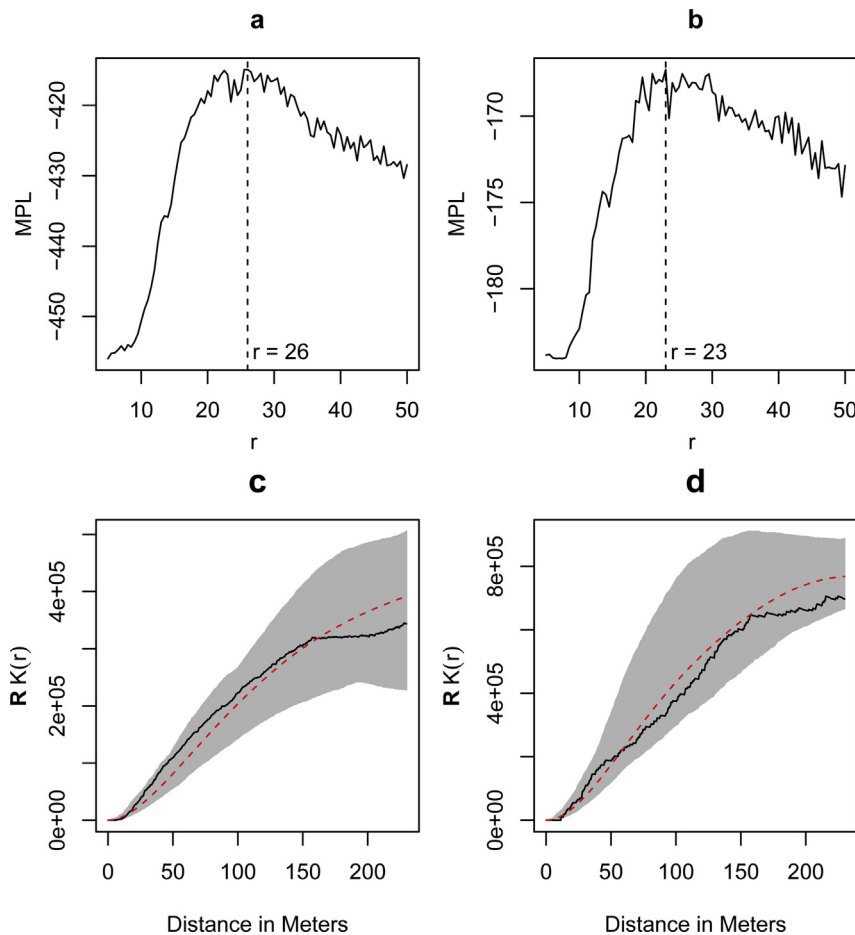
Fig. 8. Profile Maximum Pseudo-likelihood for the parameter choice in the Area Interaction model (a and b) and the residual K function of the fitted Gibbs Point Process (c and d) for the entire settlement (a and c) and the southern cluster (b and d). The maximum pseudo-likelihood has been obtained with $r = 26$ for the former, and $r = 23$ for the latter, while fitted η were 70.2 and 62.6 respectively.

with the southern settlement area. We welcome this as a possible way to approach the problem of equifinality: explicitly identifying which processes are equally likely to have produced the same observed pattern *is* a step forward. Furthermore, it should be remembered that an information-criteria approach is itself not sufficient to validate a model on its own as an acceptable explanation of the empirical record. The comparative perspective allows us only to determine which model works *better*, but does not tell us if the model is good in absolute terms. If we seek the latter task we need to rely on goodness-of-fit tests (as we did with our residual K function here), and on our own archaeological expertise. Nevertheless, this approach will remind us that our models are false, and that a better model is waiting to be formulated. We do not consider this as a limitation, but as a truthful reflection of our approach to archaeological endeavour, and an invitation to further pursue our goals.

Acknowledgements

References

Baddeley, A.J., van Lieshout, M.N.M., 1995. Area-interaction point processes. Ann. Inst. Stat. Math. 47, 601–619.

Baddeley, A.J., Turner, R., 2000. Practical maximum pseudolikelihood for spatial point patterns. Aust. N. Z. J. Stat. 42, 283–322.

Baddeley, A.J., Turner, R., 2005. Spatstat: an R package for analyzing spatial point patterns. J. Stat. Softw. 12, 1–42.

Baddeley, A.J., Rubak, E., Møller, J., 2012. Score, pseudo-score and residual diagnostics for spatial point process models. Stat. Sci. 26, 613–646.

Bailey, T., Gatrell, T., 1995. Interactive Spatial Data Analysis. Longman, Harlow.

Barrett, J.C., 2009. Book review of memory and material culture and stone worlds. Am. J. Archaeol. 113 (3), 481–482.

Beheim, B.A., Bell, A.V., 2011. Inheritance, ecology and the evolution of the canoes of east Oceania. Proc. R. Soc. B 278, 3089–3095.

Bender, B., Hamilton, S., Tilley, C., 2007. Stone Worlds: Narrative and Reflexivity in Landscape Archaeology (Publications of the Institute of Archaeology, University College London) Illustrated Edition. Left Coast Press Inc, Walnut Creek, California.

Bevan, A., Connolly, J., 2006. Multiscalar approaches to settlement pattern analysis. In: Lock, G., Molyneaux, B. (Eds.), Confronting Scale in Archaeology: Issues of Theory and Practice. Springer, New York, pp. 217–234.

Bevan, A., Connolly, J., 2013. Mediterranean Islands, Fragile Communities and Persistent Landscapes: Antikythera in Long-term Perspective. Cambridge University Press, Cambridge.

Bevan, A., Wilson, A., 2013. Models of settlement hierarchy based on partial evidence. J. Archaeol. Sci. 40, 2415–2427.

Bevan, A., Crema, E., Li, X., Palmisano, A., 2013. Intensities, interactions and uncertainties: some new approaches to archaeological distributions. In: Bevan, A., Lake, M. (Eds.), Computational Approaches to Archaeological Space. Left Coast Press, Walnut Creek, pp. 27–51.

Box, G.E.P., Draper, N.R., 1987. Empirical Model Building and Response Surfaces. John Wiley & Sons, New York, NY.

Brown, A., 1977. Late Devensian and Flandrian vegetational history of Bodmin Moor, Cornwall. Phil. Trans. R. Soc. Lond. B 276, 251–320.

Burnham, K.P., Anderson, D.R., 2002. Model Selection and Multi-model Inference: a Practical Information-theoretic Approach, second ed. Springer, New York.

Caseldine, C., 1980. Environmental change in Cornwall during the last 13,000 years. Corn. Archaeol. 19, 3–16.

Chapman, H., Gearey, B., 2000. Palaeoecology and the perception of prehistoric landscapes: some comments on visual approaches to phenomenology. Antiquity 74 (284), 316–319.

Crema, E.R., Bianchi, E., 2013. Looking for patterns in the noise: non-site spatial analysis at Sebkha Kalbia (Tunisia). In: Mulazzani, S. (Ed.), Le Capsien de Hergla (Tunisie). Culture, environnement et économie. Africa Magna Verlag, Frankfurt, pp. 385–395.

Crema, E.R., Bevan, A., Lake, M., 2010. A probabilistic framework for assessing spatio-temporal point patterns in the archaeological record. J. Archaeol. Sci. 37, 1118–1130.

Darvill, T., 2009. A review of stone worlds: narrative and reflexivity in landscape archaeology. Camb. Archaeol. J. 19 (02), 263–265.

Fortin, M.-J., Dale, M., 2005. Spatial Analysis: a Guide for Ecologists. Cambridge University Press, Cambridge.

Frieman, C., Gillings, M., 2007. Seeing is perceiving? World Archaeol. 39 (1), 4.

Gillings, M., 2009. Visual affordance, landscape, and the megaliths of Alderney. Oxf. J. Archaeol. 28 (4), 335–356.

GRASS Development Team, 2012. Geographic Resources Analysis Support System (GRASS) Software. Open Source Geospatial Foundation Project. Available at: http://grass.osgeo.org.

Herring, P., 1997. Early prehistoric sites at Leskernick, Altarnun. Corn. Archaeol. 36, 176–185.

Herring, P., et al., 2008. Bodmin Moor: Industrial and Post-medieval Landscapes. In: An Archaeological Survey, vol. 2. English Heritage, Swindon.

Hicks, D., 2009. A review of stone worlds: narrative and reflexivity in landscape archaeology. Am. Antiq. 74 (3), 590–591.

Hodder, I., Orton, C., 1976. Spatial Analysis in Archaeology. Cambridge University Press, Cambridge.

Illian, J., Penttinen, A., Stoyan, H., Stoyan, D., 2008. Statistical Analysis and Modelling of Spatial Point Patterns. Wiley, Chichester.

Johnson, N., Rose, P., 1994. Bodmin Moor: Human Landscape to c.1860. In: An Archaeological Survey. English Heritage, Swindon.

Lake, M.E., Woodman, P.E., 2003. Visibility studies in archaeology: a review and case study. Environ. Plan. B Plan. Des. 30, 689–707.

Manning, K., Stopp, B., Colledge, S., Downey, S., Conolly, J., Dobney, K., Shennan, S., 2013. Animal exploitation in the Early Neolithic of the Balkans and Central Europe. In: Colledge, S., Conolly, J., Dobney, K., Manning, K., Shennan, S. (Eds.), The Origins and Spread of Domestic Animals in Southwest Asia and Europe. Left Coast Press, London, pp. 237–252.

Markovsky, S., 2014. When survey goes east: field survey methodologies and analytical frameworks in a Central Asian context. J. Archaeol. Method Theory (in press).

Mayer, C., 2006. Making use of distances: estimating parameters of spatial processes. In: Mehrer, M.W., Wescott, K.L. (Eds.), GIS and Archaeological Site Location Modeling. Taylor and Francis, Boca Raton, pp. 148–166.

Ordnance Survey, 2013. Land-form PROFILE – User Guide and Technical Specification. Available at: http://www.ordnancesurvey.co.uk/oswebsite/docs/user-guides/land-form-profile-user-guide.pdf.

Orton, C., 2004. Point pattern analysis revisited. Archeol. Calcolatori 15, 299–315.

Palmisano, A., 2013. Zooming patterns among the scales: a statistics technique to detect spatial patterns among settlements. In: Earl, G., Sly, T., Chrysanthi, A., Murrieta-Flores, P., Papadopoulos, C., Romanowska, I., Wheatley, D. (Eds.), CAA 2012: Proceedings of the 40th Annual Conference of Computer Applications and Quantitative Methods in Archaeology (CAA). Pallas Publications, Southampton, pp. 348–356.

Penhallurick, R.D., 1986. Tin in Antiquity: Its Mining and Trade throughout the Ancient World with Particular Reference to Cornwall. Maney Publishing, London.

Premo, L., 2010. Equifinality and explanation: the role of agent-based modeling in postpositivist archaeology. In: Costopoulos, A., Lake, M. (Eds.), Simulating Change: Archaeology into the Twenty-First century. University of Utah Press, Salt Lake City, pp. 28–37.

R Core Team, 2012. R: a Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. Available at: http://www.R-project.org/.

Rowe, T.-M., 2005. Cornwall in Prehistory Illustrated Edition. The History Press Ltd, Stroud, Gloucestershire.

Schwarz, G.E., 1978. Estimating the dimension of a model. Ann. Stat. 6 (2), 461–464.

Thomas, J., 2004. Archaeology and Modernity. Routledge, London.

Tilley, C., 1996. The Powers of rocks: topography and monument construction on Bodmin Moor. World Archaeol. 28 (2), 161–176.

Vanzetti, A., Vidale, M., Gallinaro, M., Frayer, D.W., Bondioli, L., 2010. The iceman as a burial. Antiquity 84, 684–692.

Venables, W.N., Ripley, B.D., 2002. Modern Applied Statistics with S, fourth ed. Springer, New York.

Walker, M., Austin, D., 1985. Redhill Marsh, a site of possible Mesolithic activity on Bodmin Moor, Cornwall. Corn. Archaeol. 24, 15–21.