

# IV

TRA TEMPO E SPAZIO  
LA DIMENSIONE GEOGRAFICA DELLA CONOSCENZA

BETWEEN TIME AND SPACE  
THE GEOGRAPHICAL DIMENSION OF KNOWLEDGE



## POINT PATTERN ANALYSIS REVISITED

### 1. POINT PATTERN ANALYSIS AND ITS USES IN ARCHAEOLOGY

#### 1.1 *Spatial analysis and types of data*

Spatial analysis is the statistical analysis of data which include the spatial (usually two-dimensional) locations of either objects or observations. BAILEY and GATRELL (1995, 11-18) list four types of such data:

- data in which the point locations of objects is of prime interest, although there may well be additional data about attributes of the objects (e.g. their type);
- data for which point locations are chosen, and the values of certain variables are observed or measured at those locations;
- data which are only available for areas;
- data on flows which link a set of locations (areas or points).

The first type, *point-pattern data*, are the concern of this paper. The second type, *spatially continuous* or *geostatistical data*, the third type, *area data* (which have been created from the first by coarseness in the recording of locations, for example, by recording the locations of artefacts in metre squares), and the fourth type, *spatial interaction data*, are all outside the scope of this paper.

#### 1.2 *Types and scales of patterns*

Spatial patterns derive from the operation of spatial processes, and can be seen as the result of two sorts of variation in the process – global or large-scale trends (*first-order effects*) and local or small-scale (*second-order*) effects (BAILEY, GATRELL 1995, 32). The latter result from spatial dependency in the process, i.e. from a tendency for values of the process at nearby locations to be correlated with each other. In archaeological terms, this effect might show itself in the form of clusters of sites or artefacts. Many spatial patterns are the result of a mixture of these two effects.

Second-order processes can be divided into *homogeneous* (or *stationary*) processes and *heterogeneous* (or *non-stationary*) processes. A spatial process is called homogeneous if its statistical properties are independent of absolute location, i.e. if its mean and variance do not vary according to location. Full homogeneity further implies that the covariance between values at two locations depends only on the distance between them (BAILEY, GATRELL 1995, 33). Techniques of spatial analysis are usually devised to explore first-order effects and second-order variations in the mean of a process, under the assumption of homogeneity of the variance and covariance.

A further important point is that the nature of spatial patterning can depend on the scale at which it is examined. Since a spatial pattern can demonstrate completely different characteristics at different scales, any characterisation of a pattern must make it clear at which scale it has been observed. In fact, modern techniques of analysis exploit this property by seeking the scales at which certain characteristics are most pronounced.

### 1.3 *Data quality*

The quality of the data affects all data analysis, but that of point-pattern data in particular. Four main sources of error need to be considered:

- minor (“random”) errors in measurement, e.g. of location;
- major (“gross”) errors in measurement, e.g. transposition of digits or of  $x$  and  $y$  co-ordinates;
- “missing” data, e.g. failure to record location of existing objects;
- “destroyed” data, e.g. an object no longer exists at its location (e.g. a site destroyed by quarrying).

There are also issues which, although not strictly “errors”, can cause serious problems in analysis and interpretation. Variations in the precision of the recording of locations may occur, perhaps as a matter of policy (e.g. the locations of some artefact types may be recorded “exactly”, while others may be collected in bulk from grid units), or perhaps from repeated work in the same area (e.g. a pilot survey or excavation followed by a substantial one). If data are collected over a period, or by different individuals or organisations, terminology may change or “drift”, so that similar objects may be recorded in different categories depending on when or by whom they were recorded.

A further problem is that of “edge effects”; some analytical techniques are based on the assumption of a theoretically infinite study area, while of course all surveys or excavations are defined by boundaries or “edges”. The need to modify techniques to allow for such effects has been a major theme in spatial analysis.

### 1.4 *Uses in archaeology*

The extent of such problems in any particular dataset will not only affect the choice of technique, but will also determine the suitability of the dataset for spatial analysis at all. In practice, this means that spatial analytical techniques are best suited to small discrete datasets, preferable collected by a single individual or organisation over a relatively short period of time. This argument favours the use of intra-site spatial analysis over inter-site or regional spatial analysis, and this paper will concentrate on the former, although many of the points to be made would also be appropriate for the latter if the quality of the data were adequate.

## 2. HISTORY OF ANALYTICAL TECHNIQUES AND THEIR USES

### 2.1 *Early approaches in ecology*

Early applications of point-pattern analysis were made in the field of ecology, and were intended to detect departures from a random (*Poisson*) spatial distribution, in the direction of either a regular (*uniform*) distribution or a clumped (*aggregated*) distribution. Two broad approaches were favoured: one based on counting the occurrences of “objects” in the units (*quadrats*) of a grid (GRIEG-SMITH 1952; 1964) and one based on the distance from an object to its “nearest neighbour” (CLARK, EVANS 1954). The latter (*nearest-neighbour analysis*) required more precise recording of locations than the latter (*quadrat analysis*), and was more prone to difficulties caused by edge effects. One advantage of nearest-neighbour analysis was that it could be applied to a sample of locations, so that not all the available data had to be recorded. Both approaches were scale-dependent – quadrat analysis could only detect patterns of a scale at or above the size of the grid units, while nearest-neighbour analysis could only detect patterns that existed at a very small scale. A development of quadrat analysis, known as *dimensional analysis of variance*, attempted to detect the scale as well as the existence of patterning by successively analysing counts in 1, 2, 4, 8, ... contiguous grid units (WHALLON 1973; MEAD 1974).

These techniques all concentrated on the distribution of a single type of object, a severe limitation. Techniques for examining relationships between distributions of more than one type were provided by PIELOU (1969).

### 2.2 *Spatial analysis in archaeology*

Pioneering attempts to apply such techniques in archaeology (for example, DACEY 1973; WHALLON 1973; 1974) were reviewed in a general study of spatial analysis in archaeology (HODDER, ORTON 1976). This also included ideas and techniques “borrowed” from geography, and applied at regional level, in contrast to the ecological models which tended to be applied at intra-site level.

### 2.3 *Further archaeological approaches*

The following years saw a rapid growth in the range of both techniques and applications of point-pattern analysis in archaeology. For the first time, some of the techniques had been devised by archaeologists for use in archaeology. The most innovative was probably *local density analysis* (LDA) (JOHNSON 1977), which examined distances between the locations of objects of the same and of different types over a wide range of chosen scales, thus overcoming the scale-dependency of earlier techniques. It was criticised (prob-

ably unfairly) for allowing the possibility that the distributions of two types could be more closely associated with each other than with themselves (GRAHAM 1980) and was little used in archaeology. A more traditional range of “ecological” techniques was employed by CLARK *et al.* (1977), while *cluster analysis*, with a long history as a classificatory technique, was employed as a tool for point-pattern analysis by KINTIGH and AMMERMAN (1982).

Through these years, attention was focussing more closely on the intra-site scale as the above criticisms of analysis at broader scales became more apparent, culminating in a very useful collection of papers edited by HIETALA (1984). The greatest potential was that of BERRY *et al.*'s (1984) *permutation procedure*, which took the locations of all objects on a site as given, and studied the allocation of different types of objects to those locations. This overcame many of the problems traditionally associated with point-pattern analysis (e.g. edge effects, regularity brought about by the size of objects such as grave cuts), but has been surprisingly little used in archaeology. A contrasting approach was provided by WHALLON (1984) in his account of *unconstrained clustering* (UC). This sought to define areas, of any shape, in which there was a broadly similar assemblage of object types. It overcame the problem that earlier techniques had been constrained to detect square or circular patterns, but it tended to introduce spurious patterns through its reliance on data-smoothing at an early stage in the analysis.

DJINDJIAN (1988) reviewed progress in intra-site spatial analysis, and suggested a new method: *intrasite spatial structure* (ISS). This was similar to UC in some respects, but improved on it by sampling the density vector matrix (UC used the whole matrix) and analysing it by correspondence analysis before applying cluster analysis. A more comprehensive review was undertaken by BLANKHOLM (1991), who put forward another technique, the *Presab* (presence/absence) method (PA). As its name suggests, PA used presence/absence data rather than absolute quantities, and then combined some aspects of both LDA and UC. The latest statistical technique to be suggested as a tool for spatial analysis is *kernel density analysis* (BARCELÓ 2002, 244), in the context of a very thoughtful discussion of the relationship between archaeological theory and spatial analysis. However, the use of this technique seems to pre-judge some of the questions about the nature of the spatial distribution being studied, as it contains a strong and arbitrary element of smoothing, which may not always be appropriate.

## 2.4 *Developments in statistical theory*

While these developments were taking place in archaeology, there were parallel developments in statistical theory, associated in Britain with RIPLEY (1976; 1977; 1981) and DIGGLE (1983; 2003). They were based on the idea of modelling the stochastic processes that produce spatial patterns, and in-

roduced the *K function* as a tool for characterising spatial patterns. The *K function* can be defined by

$$\lambda K(h) = E(\#(\text{events within distance } h \text{ of an arbitrary event})),$$

where  $\#$  means “the number of”,  $E(\ )$  denotes an expectation, and  $\lambda$  is the *intensity* or mean number of events per unit area (assumed constant) (BAILEY, GATRELL 1995, 92). A related function, the *L function*, was found to be a useful indicator of clustering at particular scales (BESAG 1977). It was defined by

$$\hat{L}(h) = \sqrt{\hat{K}(h)/\pi} - h \text{ (BAILEY, GATRELL 1995, 94).}$$

Initially, the *K function* was defined for the distribution of a single type, but the bivariate function, the *cross K function*, was later defined by

$$\lambda_j K_{ij}(h) = E(\#(\text{type } j \text{ events } \leq h \text{ of an arbitrary type } i \text{ event})),$$

with the analogous *cross L function*

$$\hat{L}_{ij}(h) = \sqrt{\hat{K}_{ij}(h)/\pi} - h \text{ (BAILEY, GATRELL 1995, 120-121).}$$

These functions are surprisingly similar to Johnson’s LDA, but their exploratory use was based on a plot of *K* or *L* against *h*, looking for peaks (indicating clustering at scale *h*) or troughs (indicating regularity at scale *h*) in the *L function*. Edge effects were recognised and accommodated into the theory, and it became possible to calculate confidence zones for *K* and *L*, so that the significance of any observed clustering or regularity could be assessed (BESAG, DIGGLE 1977).

A natural development would be to relax the conditions under which techniques such as *K* and *L* functions could be used. Their use is based on the assumption of a homogeneous and isotropic point process; there may well be reasons in practice why such an assumption does not hold. PÉLISSIER and GOREAUD (2001) suggested a three-stage approach to such problems:

- detection of possible heterogeneity through the observation of a peak in the *L function* at large scales;
- division of the study area into homogeneous sub-regions;
- separate analysis of each sub-region.

They also demonstrated a useful tool (proposed by GETIS, FRANKLIN 1987) of mapping the values of  $L_i(h)$  across a study area to show local variation at a range of scales. The case studies of their applications are entirely ecological, concerned with forestry.

### 3. TEACHING NEEDS AND THE SEARCH FOR SOFTWARE

#### 3.1 *Teaching spatial analysis in a GIS context*

As part of University College London Institute of Archaeology's MSc degree programme *Geographical Information Systems and Spatial Analysis in Archaeology*, the course G117 *Spatial Analysis in Archaeology: sources, sampling and statistics* was instituted for the 2000/2001 session. The choice of a core text for the statistical aspects of the course was easy – BAILEY, GATRELL 1995 met all the needs. It covers the analysis of point-pattern, spatially continuous and area data, with plenty of worked examples to show how various techniques can be used. None of the example are drawn from archaeology, but that does not detract from the book's value.

The choice of software too seemed automatic; the package INFO-MAP is included on a floppy disk with BAILEY, GATRELL 1995, and can easily be installed on a PC. It is intended to illustrate the use of various techniques described in the book, and is accompanied by the datasets that form the book's case studies. Registration with the author provides a key which permits the creation of new datasets.

Three datasets were created, one for each of the main types of data. They were based on the Barmose I site for point-pattern data (BLANKHOLM 1991; see below), phosphate data from the Laconia Survey (BUCK *et al.* 1988) for spatially continuous data, and, for area data, annual counts of archaeological interventions in the City of London and the 32 London Boroughs, taken from the *Excavation Round-up* of the «London Archaeologist» magazine. Creation was straightforward, though rather time-consuming, especially defining the boundaries of the London Boroughs.

#### 3.2 *Experiences of INFO-MAP*

The drawbacks of INFO-MAP started to appear when it was used for teaching in a laboratory setting. The package has a DOS interface which, although it did not trouble the staff (who had lived through the DOS phase of computing), was unfamiliar to most of the students, who had been brought up on Windows interfaces and knew nothing else. A more fundamental problem was that INFO-MAP was restricted to run within the 640Kbytes of conventional DOS memory (BAILEY, GATRELL 1995, 406). It frequently exceeded this limit and then crashed. Somehow the students managed to complete their projects, but the experience had been a bad one for all concerned, and the search was on for different software for the following year.

It soon became clear that we were unlikely to find one affordable software package that would analyse all three classes of data. Spatially continuous data were well catered for, probably because of their applications in geol-



ogy and the exploration for mineral resources. Software for point-pattern analysis was harder to find; the *Arcospace* package (BLANKHOLM, PRICE 1991) seemed to be no longer available, and an obvious choice of package, *Splancs* (DIGGLE, ROWLINGSON 1993), was ruled out because it required the presence of an expensive general statistics package (S+) to enable it to run. A candidate was found in the ADS module (*Spatial Data Analysis*) in the package ADE-4 (*Ecological Data Analysis*) produced by the University of Lyons, France and available at <http://pbil.univ-lyon1.fr/ADE-4/ADE-4.html>. A copy was acquired, evaluated and installed in time for teaching in the 2001/2002 session. It has since also been used for teaching in 2002/2003 and 2003/2004.

### 3.3 ADE-4 (ADS) – *what it is and what it does*

The ADE-4 package is a set of tools for exploratory data analysis, which can run on either Windows or MacOS *via* a slightly unusual *Metacard* interface. Most modules are bilingual (French and English). Since 2001 it has been possible to install the package on a network server. So far, only the ADS module has been used at the Institute of Archaeology, reflecting the need for point-pattern analysis. Many of the other functions of the package can be met by more widely-used software such as SPSS and Minitab.

The ADS module contains three programs: *Ripley* (for univariate analysis), *Intertype* (for bivariate analysis) and *ADSutil* (for data manipulation). Various plotting routines within the package, such as *Curves* and *Plot*, are used to display the output. *Ripley* calculates  $K$  and  $L$  functions and the data needed to map the  $L$  function across the study area. *Intertype* calculates cross  $K$  and  $L$  functions and enables the cross  $L$  function to be mapped. Edge effects are dealt with according to GOREAUD and PÉLISSIER (1999), and the general approach is as described by them (GOREAUD, PÉLISSIER 2001). The programs are well documented with worked examples, and students had no problems in adjusting to the interface and using the software.

## 4. THE CHOICE OF A DATASET FOR TEACHING

### 4.1 *Requirements for a teaching dataset*

A dataset to be used for teaching the techniques of point-pattern analysis should meet the criteria of data quality given above (§ 1.3). In addition, it should be large and complex enough to be “interesting” and not trivial, while not being so large as to create problems of analysis due to sheer size. If possible, it should already exist in digital form, but digitisation should not be ruled out by its size. Finally, a “real” dataset is preferable to an artificial or simulated one, provided that the data appear to relate to a single phase of occupation. A published dataset can provide useful alternative analyses for purposes of comparison.

#### 4.2 The chosen site – Barmose I

The chosen dataset was from the site of Barmose I, an early maglemosian (mesolithic) site dated c. 7500-6000 B.C. and located in Barmosen (Barmose Bog) in South Zealand, Denmark (JOHANSSON 1971; 1990). The excavated area was almost 100 sq.m., in a rather irregular shape (see Fig. 3). There is some evidence for the presence of a hut floor with a single internal hearth, but its outline can only be approximated (BLANKHOLM 1991, 185). It appeared to meet the criteria for a teaching dataset given above. All artefacts, tools and ecofacts were recorded in three dimensions to the nearest centimetre, from a “culture layer” up to 5 cm thick.

The dataset consists of the location and class of each of 473 flint artefacts that had been plotted exactly. Three locations were found to be outside the excavated area, and have been removed from the dataset, reducing the total to 470 and the numbers in each class to those shown below. Counts of débitage by grid squares were also available, but were not used for teaching purposes. The data were stored as a tab-separated text file with three columns: *x*-coordinate, *y*-coordinate, class type. The class codes and counts of artefacts are as follows:

Class code	class	abbreviation	count
1	scraper	SCR	38
2	burin	BUR	25
3	lanceolate microlith	LAN	36
4	microburin	MIC	16
5	flake axe	FLA	28
6	core axe	CAX	4
7	square knife	SQK	192
8	blade/flake knife	KNI	16
9	denticulate/notched	DEN	26
10	core	COR	80
11	core platform	CPL	9

The dataset has been analysed by BLANKHOLM (1991, 183-205) using the techniques of K-means Cluster Analysis, Unconstrained Clustering, Correspondence Analysis and Presab.

The use of ADS implied a repetitive use of its programs, since *Ripley* had to be run for each tool class and *Intertype* for each pair of classes. In a teaching situation, this repetition can be reduced by dividing up the work amongst the students. For example, in 2002/2003 each of eight students was given a class (three rare types, 4 – microburin –, 6 – core axe – and 11 – core platform – were omitted), and ran *Ripley* for that class with *Intertype* for its relationship with each other class. The results were photocopied and a complete set was distributed to each student for their writing up. The following analyses and discussion are based on this work, and I am grateful to all the students who took part.

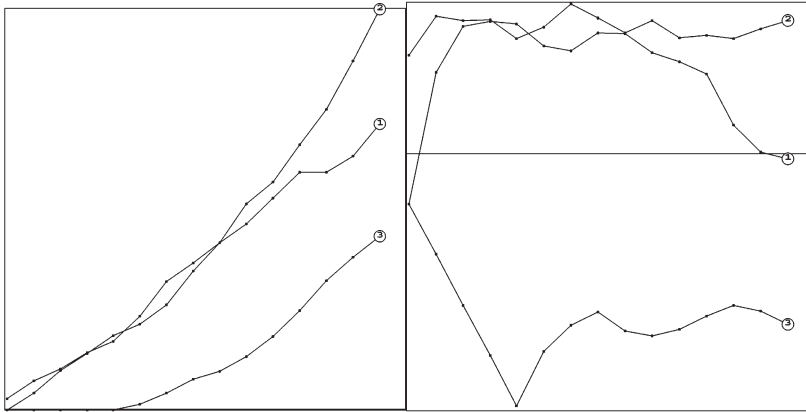


Fig. 1 – (left) Example of a  $K$  function: burins in the densezone; (right) The corresponding  $L$  function. The horizontal interval are 0,1 m; curve 1 represents the data and curves 2 and 3 delimit a confidence zone for a uniform distribution. Evidence of aggregation can be seen between 0,6 and 0,9 m.

## 5. COMPARATIVE ANALYSES OF THE DATASET

### 5.1 Patterns revealed at Barmose I

The analyses comprised:

- a  $K$  function and an  $L$  function for each class;
- a map of the  $L$  function for each class;
- a cross  $K$  function and a cross  $L$  function for each class with each other class;
- a map of the cross  $L$  function for each class with each other class.

The functions were plotted at 0,1 m intervals from 0,1 m to 3,0 m, and maps of the  $L$  functions and cross  $L$  functions were produced at the same interval. This produced a wealth of graphical output to be interpreted. Examples of a  $K$  function, an  $L$  function and a cross  $L$  function map are shown as Figs. 1-2.

The first step in the interpretation was to look at the  $K$  and  $L$  functions. The values of the functions for  $h = 0,1$  m were ignored, as they could be unduly influenced by rounding in the recording of locations. The functions revealed strong aggregation at large scales for all classes, a clear indication of spatial inhomogeneity in the data, and an indication that the space should be divided for finer-grained analysis. Nevertheless, the cross functions were examined and the patterns found are shown in Tab. 1.

A salient feature of this table is the high proportion of relationships that show neither significant aggregation nor significant segregation. Aggregation between two classes is rare, occurring only between burins and blade knives (at scales above 2,2 m), and between cores and various classes (scrap-



Fig. 2 – The  $L$  function map corresponding to Fig. 1. Each symbol represents the location of a burin. Hollow squares indicate “low”  $L$  values (i.e. segregation), and shaded circles represent “high”  $L$  values (i.e. aggregation). The size of the symbol reflects the strength of the pattern. The “thumbnail” maps are at 0,1 m intervals of  $h$ , from  $h = 0,1$  m (top left) to  $h = 1,5$  m (bottom right). Strong aggregation can be seen between  $h = 0,6$  and  $h = 0,9$  m, but even here some burins (to the west) are segregated.

ers, microliths and blade knives) at scales above 2,5 m. Flake axes stand out as consistently segregated from other classes; the exception being with blade knives (which may just reflect how few blade knives there are).

The maps of the  $L$  functions for each class show a central core of positives (more neighbours than expected) surrounded by a periphery of negatives

		Local class							
		SCR	BUR	LAN	FLA	SQK	KNI	DEN	COR
Base class	SCR	-	S 0.5m	ns	S 0.4-0.6m	S 0.4-0.6m	ns	S 0.5-0.8m	S 0.4-0.5m
	BUR	ns	-	S 0.5m	S 0.3-0.4m 1.8m	ns	A 2.2- 2.8m	ns	ns
	LAN	ns	ns	-	S >2.0m	ns	ns	ns	ns
	FLA	S 0.4-0.7m	S 0.6-1.9m	S >1.0m	-	S >1.5m	ns	S >0.9m	?
	SQK	S 0.4-0.6m	ns	ns	S 0.2-0.5m 1.6-2.1m	-	ns	ns	S <1.0m
	KNI	ns	A >2.3m	ns	ns	ns	-	ns	ns
	DEN	S 0.5m	ns	ns	S >0.4m	ns	ns	-	ns
	CO R	S 0.4-0.7m A 2.5-2.6m	ns	S <0.7m A >2.5m	A 0.7m	S <1.0m	A 1.7m, >2.6m	ns	-

Tab. 1 – Relationships between tool classes across the whole site, as expressed by the  $K$  and  $L$  functions. A = aggregated, S = segregated (the numbers show the scales at which these occur), ns = no significant relationship.

(fewer neighbours than expected). The map of the  $L$  function for all classes taken together shows a strong central core area in the north-central part of the site, reinforcing the interpretation of inhomogeneity. It overlaps, but does not coincide with, the area interpreted by Blankholm as the hut floor (Fig. 3). The core area extends beyond the floor to the north, but does not include the western part of the floor. Potential patterning in both the core area and the periphery is obscured by the strong contrast between these two areas.

To proceed further, separate analyses of the core and outer (peripheral) areas are needed. The boundary between the core area (*densezone*) and the periphery (*outerzone*) was determined by visual inspection of the maps of the  $L$  functions, together with plots of artefact classes. More sophisticated approaches to this division (RIPLEY, RASSON 1977) were felt to be unnecessarily complicated here. There was a practical problem, in that while ADSUtil could define the densezone, it seemed unable to define the outerzone as the part of the excavated area outside the densezone. Instead, the outer edge of the outerzone had to be defined as a rectangular “sampling window” encompassing the whole excavated area.

The Ripley analyses of the densezone (carried out at up to  $h = 1,5$  m) showed aggregation for burins, flake axes, square knives, cores and possible scrapers. In each case maximum aggregation seems to occur around  $h = 0,6$  to  $0,8$  m. There are no instances of segregation (uniformity), except possibly for scrapers at  $h > 1,0$  m. The maps of the  $L$  functions show that the classes which show aggregation do so in different parts of the densezone; scrapers in

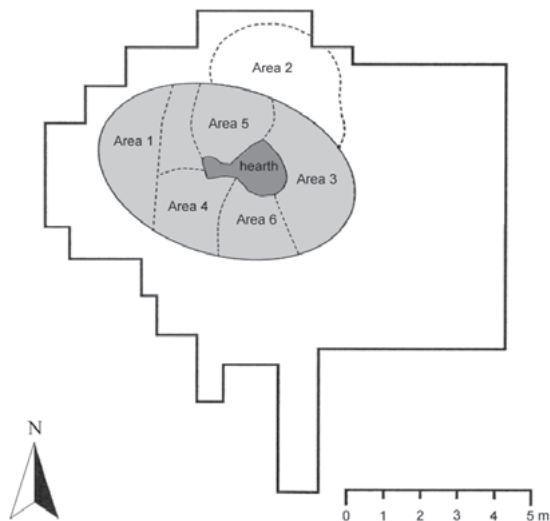


Fig. 3 – Site plan, showing possible zoning of the densezone and hut floor area (after Reynolds).

the north, south-west and south-east, burins in the south-centre, flake axes in the west, square knives in the north-centre and cores in the east.

The Ripley and Intertype analyses of the densezone are summarised in Tab. 2. As in Tab. 1, aggregation between two classes is rare, occurring only between burins and microliths, and possibly between microliths and denticulates (in both cases at scales above 1,3 m). Flake knives are the most consistently segregated class (showing segregation from burins, square knives, denticulates and cores at various scales), followed by scrapers which show segregation from microliths, square knives and cores. In contrast, blade knives show no significant relationships with other classes (which may just reflect how few they are).

The corresponding analyses for the outerzone (Tab. 3) are more difficult to interpret, because:

- some “spurious” aggregation can be expected because of the inclusion of blank areas outside the excavation (p. 309);
- the small numbers of objects in some classes in the outerzone may cause spurious apparent segregation at small scales;
- the small numbers of objects in some classes in the outerzone mean that some patterns may not achieve statistical significance.

Nevertheless, some patterns are evident: three classes (flake axes, square knives and cores) show clear aggregation, as well as segregation from other classes. They appear to be concentrated (in the outerzone) to the west and

		Local class							
Base class	SCR	A? 0.8m S? >1.0m	ns	S 0.4-0.8m	ns	S all	ns	ns	S 0.5m
	BUR	ns	A 0.6-0.9m	ns	S 0.5-0.8m	ns	ns	ns	ns
	LAN	ns	A >1.3m	ns	ns	ns	ns	A? >1.3m	ns
	FLA	ns	S 0.5-1.1m	ns	A 0.3-1.0m	S 0.1, 0.4m >1.4m	ns	S 0.5m	S 0.4m
	SQK	S 0.2m >1.3m?	ns	ns	S 0.2m >1.4m	A 0.2-1.3m	ns	ns	ns
	KNI	ns	ns	ns	ns	ns	ns	ns	ns
	DEN	ns	ns	ns	S 0.4, 0.8m	ns	ns	ns	ns
	CO R	S 0.4, 0.6m	ns	ns	S 0.3m	ns	ns	ns	A 0.7m

Tab. 2 – Relationships between tool classes in the densezone, as expressed by the *K* and *L* functions. The diagonal elements refer to the Ripley analyses.

A = aggregated, S = segregated (the numbers show the scales at which these occur), ns = no significant relationship.

		Local class							
Base class	SCR	ns	ns	ns	ns	ns	ns	ns	ns
	BUR	ns	ns	ns	ns	ns	ns	ns	ns
	LAN	ns	ns	ns	ns	ns	ns	ns	ns
	FLA	ns	ns	ns	A 0.3m, 0.6-2.0m	S 0.2m	S?	1.5m	ns
	SQK	ns	ns	ns	S 0.2m	A all	ns	ns	S 0.3-0.6m
	DEN	ns	ns	ns	S? >1.3m S 1.7m	ns	ns	ns	S 1.4-1.5m
	CO R	ns	ns	ns	ns	S 0.4m	S 0.6-1.7m	ns	A all

Tab. 3 – Relationships between tool classes in the outerzone, as expressed by the *K* and *L* functions. The diagonal elements refer to the Ripley analyses. Blade knives have been omitted because they are too few.

A = aggregated, S = segregated (the numbers show the scales at which these occur), ns = no significant relationship.

well east of the densezone (flake axes), mainly south but also south-west of the densezone (square knives) and west and north-west of the densezone (cores). Also, denticulates may be aggregated south of the densezone, through they do not achieve formal significance.

method	number of clusters	number of activity areas	
		inside hut	outside hut
Visual inspection	7	3	4
K-means	7	3	4
UC	15	4	7
CA	16	4	5
PA (coordinate)	19	6	9
PA (grid)	15	5	5

Tab. 4 – Summary of outcomes of Blankholm’s analyses.

### 5.2 Comparison with original analyses

Blankholm’s analyses used different methods to divide the site into clusters, based on the similarity of artefact distribution patterns, which were then interpreted by the author into a smaller number of activity areas. A summary of the outcomes is given as Tab. 4. In general, each area contains parts of more than one cluster, and many clusters belong in part to more than one area. The delineation of activity areas is thus an interpretative rather than a quantitative procedure.

In his conclusion, BLANKHOLM (1991, 203) compared these outcomes with those of JOHANSSON (1990) who subjectively defined only two activity areas. He concluded that there was a «high degree of consistency in the outcome of the application of the different methods». He noted a primary distinction between inside and outside space, the former being divided into three general multi-purpose work areas and one area of lower activity to the west, and the latter into a varying number of more differentiated and specialised areas, mostly to the south and east of the hut.

In the present analysis, the densezone overlaps, but does not coincide with, the supposed “hut floor”. The western part of the floor (Area 1), with relatively few artefacts, lies outside the densezone, while the northern part of the densezone (Area 2), characterised by an abundance of COR, SCR and SQK, lies to the north of the floor. The rest of the floor can be divided into an area east of the hearth (Area 3), characterised by an abundance of BUR, COR, DEN and SCR, an area south-west of the hearth (Area 4), characterised by an abundance of COR, FLA and SCR, and two area north and south of the hearth (Areas 5, 6) which, while densely occupied, have no particularly abundant types.

A more general insight is that, although some clusters of different types do overlap, the level of aggregation between different types or across the whole site is low. This suggests that these overlaps may be due to repeated use of the same space for different functions, rather than the association of the types together in the same function.



## 6. CONCLUSIONS

Compared to the other techniques available for point pattern analysis, the ADS approach has both advantages and disadvantages. It is good at examining variation across a range of scales, and produced rich graphical output for interpretation. It copes well with edge effects, and does not rely on data-smoothing with its tendency to create spurious patterns.

The quantity and variety of the graphical output of ADE-4 makes it very suitable for an “interactive” approach, in which specialist questions are posed and answered, the output giving rise to fresh questions. It may be less suited to providing a single definitive “result”, e.g. in terms of definitive zoning of the site.

Its main drawback is its implicit reliance on a hypothesis-testing paradigm, which is apparent in the confidence zones for the  $L$  and cross  $L$  functions, and which forms the basis of the  $L$  function maps. As always, such an approach is much influenced by sample size, and the significance of a pattern can reflect the number of artefacts in a particular class as much as the nature of the pattern itself.

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#### ABSTRACT

Point pattern analysis has been one of archaeology's quantitative approaches since at least the 1970s, and has been applied at a range of scales, from the region to the site. Various techniques have been "borrowed" from other disciplines, notably ecology, such as quadrat analysis, nearest-neighbour analysis and kernel density analysis. There have also been "home-grown" techniques such as Local Density Analysis, Presab and Unconstrained Clustering, as well as the use of Cluster Analysis itself. This paper reviews these developments, assessing their strengths and weaknesses. A statistical advance was made in the 1970s with the development of the *K* function approach. This has become embodied in the ecological statistical software package ADE-4 as the *Ripley* and *Intertype* programs. These programs were found in a search for suitable affordable software for teaching spatial analysis at post-graduate level, and have been used in this role for three years, taking as a test-bed the Danish mesolithic site of Barmose I. The outcome of this work is presented as a case study and compared with earlier analyses of this dataset. The value of ADE-4 for archaeological spatial analysis is assessed.

