31 Looking for patterns in the noise: non-site spatial-analysis in Sebkha Kelbia

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Résumé : *Dans cet article, nous nous intéressons au paysage archéologique des phases attribuables à l'Épipaléolithique/Néolithique en Tunisie, et particulièrement à la distribution des restes de surface. Les recherches archéologiques dans ce domaine se sont toujours concentrées sur l'étude des* rammadiyat, *tout en ignorant la riche dispersion superficielle, qui caractérise les zones environnantes. La finalité de cette étude est de démontrer en quelle mesure, l'adoption de techniques dites de « non-site survey », qui ont déjà garanti un discret succès dans d'autres régions de la Méditerranée, peut offrir des nouvelles perspectives pour l'étude de la préhistoire tunisienne, à travers une vision spatialement continue du paysage archéologique. En même temps, nous proposons un aperçu des plus récentes approches méthodologiques et théoriques capables d'identifier la diversité dans l'utilisation de l'espace, appliquées à une zone géographiquement limitée, au nord de la Sebkha Kelbia. Les résultats ont permis d'identifier une distribution spatiale des industries lithiques caractérisée par une structure non aléatoire. Les différents artefacts montrent des cas d'agrégation et de ségrégation à différentes échelles et sur des positions spatiales absolues.*

Abstract : *In this paper, we consider the archaeological landscapes of Epipalaeolithic/Neolithic Tunisia by focusing on the distributional pattern of surface materials. Archaeological inquiry of the area has been traditionally centred on the studies of* rammadiyat, *and neglected the surrounding dispersion of material culture. We aim to show how non-site survey techniques, which have been successful employed in other Mediterranean contexts, can provide new insights to the Tunisian prehistory. We discuss the underpinning theoretical foundation of the proposed method and then illustrate the analysis of the prehistoric human use of space of a small area at north of Sebkha Kelbia. The results show how the spatial distribution of the lithics is characterised by a non-random structure, with instances of significant aggregations and segregations between different artefact types at different scales and absolute spatial locations.*

Riassunto : *In questo articolo viene considerato il paesaggio archeologico delle fasi riferibili all'Epipaleolitico/Neolitico in Tunisia, focalizzandosi sul pattern distribuzionale dei resti in superficie. Le ricerche archeologiche in quest'ambito si sono tradizionalmente concentrate sullo studio delle* rammadiyat, *spesso ignorando la ricca dispersione superficiale che caratterizza le aree circostanti. Scopo di questo contributo è quello di dimostrare come l'adozione delle tecniche di "non-site survey", che hanno già garantito un discreto successo in altre aree del Mediterraneo, possa offrire nuove prospettive allo studio della preistoria tunisina. Allo stesso tempo, si vuole offrire una panoramica dei più recenti approcci metodologici e teorici capaci di identificare le diversità nell'uso dello spazio, applicati ad una piccola area a nord della Sebkha Kelbia. I risultati hanno identificato una distribuzione spaziale dell'industria litica caratterizzata da una struttura non-random, con casi di aggregazione e segregazione tra diversi tipi di artefatti su scale e posizioni spaziali assolute.*

> "[…] site, as an *archaeological concept*, has no role to play in the discipline. Its uses are not warranted by its properties. It obscures critical theoretical and methodological deficiencies, and it imparts a serious and unredeemable systematic error in recovery and management programs. In spite of the technical problems its abandonment will cause, the concept of archaeological site should be discarded." (emphasis original, Dunnell 1992: 37)

Introduction

In a seminal paper published about 20 years ago, Robert Dunnell (1992) reviewed the limits of the notion of archaeological "site", and proposed the radical and provocative solution to abandon its use. Although such an extreme resolution has not been embraced, several archaeologists shared more or less similar views and conducted "siteless", "non-site", or "off-site" surveys since the late eighties (Gallant 1986; Wandsnider &

Ebert 1986; Wilkinson 1989; Davis 2004; etc.), with a clear transition from a site-based to an artefact-based perspective. A recent review by Caraher and colleagues (Caraher *et al.* 2006) suggests how such a shift in the analytical unit emerged from different reasons: 1) the quantitative characterisation of "off-site" areas to enhance the formal definition of "site" extents; 2) an explicit interest on the "full range of human behaviour across the landscape" (*ibid.*: 8); and 3) a complete rejection of the notion "site" derived by an awareness of the methodological and epistemological limits resulting from its adoption. Although the three approaches have some dissimilarities (*e.g.* an "off-site" archaeology still acknowledges the existence of "sites" as an archaeological concept), stemming from different underpinning research questions and datasets, they share the view of a continuous nature of the archaeological landscape, where crisp and tangible definitions of the spatial extent of a "site" are problematic even in the best case.

The adoption of different analytical strategies is not exclusively rooted to the properties of the objects we seek to study. It is also determined by the way we conceive reality and by our ultimate aims and interests. Thus, if the primary objective is centred on the identification of stratified "sites", then the surrounding surface scatters of artefacts (the "background noise"; Gallant 1986) will be virtually ignored. From such a standpoint, landscapes will ultimately be conceived as empty spaces filled with ambiguously defined "islands" of peaks in artefact density.

Despite numerous discussions on how such a vision is heavily biased by the hegemony of a specific subset of archaeological data (see Foley 1981), Tunisian archaeology is still mainly affected by a site-based paradigm. A recent comparative review of field surveys in Tunisia (Stone 2004) has shown that only four projects employed non-site surveys (Dougga Survey, De Vos 2000; Jerba Survey, Frentress 2000, 2001; Leptiminus Survey, Mattingly 1992; Mattingly *et al.* 2000; Stone *et al.* 1998; Segermes Survey, Dietz *et al.* 1995; Ørsted *et al.* 2000), and only one of these recovered prehistoric artefacts (the Segermes Survey, see Zoughlami 1995). If we ignore this exception and a small-scale surface collection at Faïdh el Nadhour (Chenorkian *et al.* 2002: 68-79), prehistoric survey activities in Tunisia have been primary focused on finding dots in the landscape.

Two reasons are likely to underpin such a lack of epistemological revision in Tunisian hunter-gatherer archaeology. First, landscape surveys aimed primarily to identify stratified sites to be excavated or conserved, and less emphasis has been placed on understanding the spatial properties of the anthropic landscape. Second, the predominance of *rammadiyat* (see Mulazzani 2010 for discussions) as unique landmarks in the prehistoric landscapes has marginalised the importance of any other instances of surface materials, which consequently have never been approached through formal investigations.

The aim of this paper is to focus on such neglected portions of Tunisian landscapes. Survey activities of the first few seasons of the project (2002-2005) have indicated how a site-based survey is often unpractical due to the heterogeneous nature of artefacts clusters (different size, shape, and density), which leads to problematic choices in defining what is a site and what is not. In order to solve this issue, we conducted a *non-site* survey strategy where we sampled artefacts through an arbitrary defined 20-meter grid structure and shifted our unit of analysis from sites to artefacts.

For the present paper, we aim to tackle the following three points: 1) assess whether the distribution of artefacts surrounding the *rammadiyat* are characterized by spatial clusters or are an homogenous background noise; 2) identify the nature of the spatial relationships between different artefact types; and 3) determine whether this vary across space.

Section 2 (*Data collection*) will briefly describe the location of the case study area and the data collection method adopted in the 2006 survey campaign. Section 3 (*Theory and method*) will undertake a short review of the analytical methods adopted in previous studies and describe the techniques adopted for this project. Section 4 (*Results*) will describe the set of data categories we decided to explore and illustrate the results of our analyses. Section 5 (*Discussion*) will then discuss these in relation to the research questions stated above, and finally section 6 (*Conclusion*) will present our conclusions.

Data collection

The four previous campaigns of surveys (2002-2005) have been focused on the coastal area (2002), the shores of *Sebkhet Halk el Menjel* (2002-2004), along *Oued Manfas es-Sod* (2005), and on the hills north and north-east to the modern town of *Sidi Bou Ali*. In all cases, the primary aim was the identification of prehistoric *rammadiya,* and consequently, survey strategies were primarily designed to identify high density clusters of artefacts (stone tools and ostrich eggshell fragments) associated with burnt stones, dark soil, and shell fragments (see Camps 1997). During these fieldwork campaigns, the presence of "off-site" scatters of artefacts has been noticed, strongly suggesting the necessity of a revision in the sampling strategy.

To explore the spatial structure of such a "background noise", two areas at the western and eastern edges of *Sebkha Kelbia* have been purposely investigated. The present study will focus on one of these, located near the modern village of *Bir Jedid* (*Fig. 31.1*), close to *Oued Zahzam* (*ca* 200 meters at east). The most

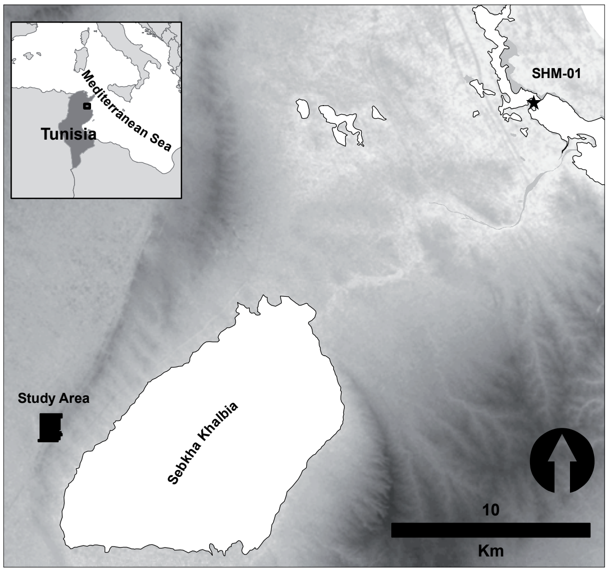

Fig. 31.1. Location of the study area. The background DEM has been obtained from ASTER GDEM (property of METI and NASA).

notable geographic feature of the area is a rocky crest (*ca* 30-40 meters higher than the surrounding lowland) crossing the study area from southwest to northeast between the Oued and the Sebkha.

The entire region surrounding *Sebkha Kelbia* has been first divided into a 20-meter resolution grid, each with a unique identification code from which the spatial location of the grid centroid can be retrieved. The present case study is formed by 3574 of these square grids, covering an area of 142.96 hectares.

The survey has been conducted with a team of 5 individuals displaced with a fixed inter-distance of 8 meters. This allowed the observation of two rows of grid for each walking transect. All observed archaeological material has been collected and attributed to a unique grid location. The total number of recovered artefacts exceeded 37,000 units, with the majority being artefacts in flint, followed by smaller proportions of lithics in sandstone and limestone, and fragments of ostrich eggshells.

While the collection of artefacts was based on "non-site" principles, we still adopted conventional criteria for the identification of seven high-density clusters of artefacts recognized as "site". Among these the largest concentration (with *ca* 86% of the total number of artefacts) on the north-eastern portion of the study area, labelled SEK-11, has been excluded from the current study, in order to focus more directly on the low density background scatters of artefacts. Detailed account on the material culture recovered at SEK-11, along with a site-based comparison with the surrounding local archaeological landscapes can be found in chapters 32 and 33 of this volume.

Theory and method

The shift from a site-based to an artefact-based approach could require a sacrifice in term of accuracy and precision in the spatial definition of the individual data[1]. In our case, artefact positions are approximated to the grid location, and thus spatial relationships between objects below the resolution of the grid size remains unknown. Furthermore, accuracy was slightly affected by the limits imposed by the GPS definition of the grid edges, which is usually in the range of *ca* ±3 meters.

The majority of spatial analyses of surface data collected by regional surveys are centred on the definition of an imposed spatial partition (*i.e.* fields and transects) or an artificial *ad hoc* structure (*i.e.* grids). These analytical units are described by summary statistics, and the ultimate goal of the spatial analysis becomes the quantitative assessment of their spatial structure. This could take the form of basic methods such as the *Mean to Variance Ratio* adopted by Ebert (1992) or to more advanced geostatistical or regression-based methods where artefact distributions are compared to environment data (see Bevan & Conolly 2009). In either case, the basic unit of analysis is not the single artefact but aggregates of artefacts framed by an artificial spatial structure.

One of the main problems of such an approach is the so-called *modifiable areal unit problem* (MAUP; Openshaw 1984), which basically states how different artificial spatial structures might determine different analytical outcomes. The criteria by which we aggregate our data (e.g. through predefined grids, transects or even arbitrary defined "sites") will in fact lead to the imposition of a specific *scale* and *partition* (or zoning) of space (Jelinski & Wu 1996), which in turn will partially drive the analytical output and its interpretation.

In order to overcome at least some of these issues, we need to shift our analytical unit from the aggregate field based data to the single artefact location. This will be in line with the general philosophy of the site-less analysis of the landscape, providing an epistemic shift which is not limited to the data collection but also to the analytical aspects of the research.

The direct application of such an approach is not trivial. The *partition* problem has been tackled by our sampling strategy which, by choosing an artificial 20m grid structure, had minimised the potential bias that might have arose from differently shaped and sized units of analysis. Recording the precise location of each

1 It is worth reminding that a site-base approach will still be subject to constrains derived from the arbitrary choice of a single point location, or the subjective definition of a polygonal "boundary". Both instances will determine a loss of information and will be biased by subjective criteria.

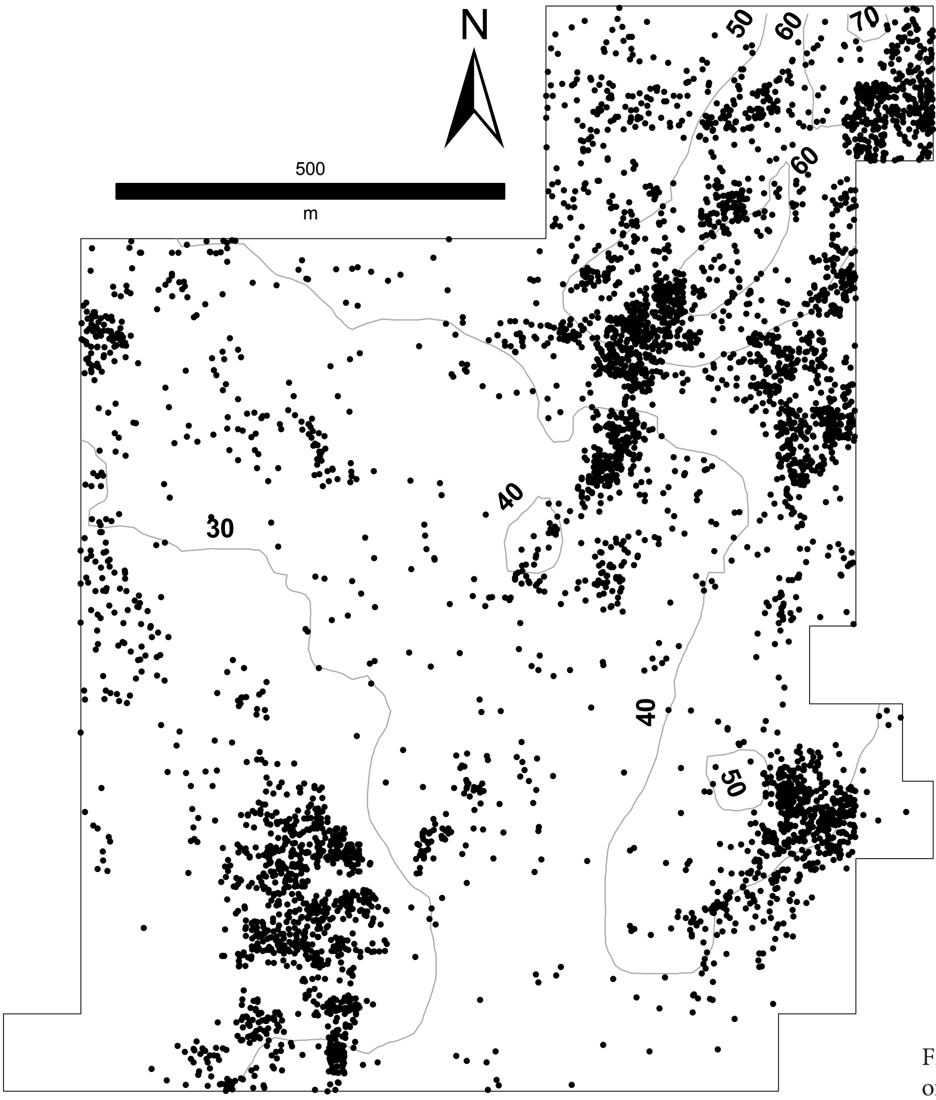

Fig. 31.2. Simulated distribution of stone tools on the study area.

artefact could theoretically solve the *scale* problem. This, however, requires an unpractical collection strategy once the survey area becomes large.

An alternative solution consists of *simulating* the artefact positions, providing for each a spatial constrain defined by the boundary of its attributed square, and then analyse these (*Fig. 31.2*). We can calculate the accuracy of such an approach by predicting the spatial variation between the empirical observed data and its simulated counterpart. One way to do this is to simulate two random points. The first will represent the observed location of an artefact while the second will represent its simulated point (*Fig. 31.3-a*). We can calculate the inter-distance between such a pair, and then repeat this multiple times. The so-obtained distribution will provide a probabilistic assessment of the displacement error between the original and the simulated location of an artefact. *Figure 31.3-b* shows this with 100,000 simulated random points, and suggests that the displacement error is below 18.56 meters 95% of the time. An alternative approach consists of measuring the difference between the inter-distance of a pair of observed points and its simulated counterpart. We can do this by simulating two pairs of points, the first representing the empirical data, and the second its simulated counterpart (*Fig. 31.3-c*). *Figure 31.3-d* shows the distribution of such inter-distances for 100,000 pairs. This time the histogram has a strong, positive skew, with a lower 95th percentile at 13.52 meters. These results allow us to measure the accuracy of the point data and imply that as long as we confine our interpretations to spatial scales above these figures, we can safely ignore that fact that we are analysing simulated rather than actual locations of the artefacts.

The adoption of a comparatively fine-grained grid-based sampling strategy and the simulation of artefact locations does not fully overcome some of the limits of MAUP, but nonetheless provides a framework that allow us to adopt a variety of point-pattern analysis (Diggle 2003; Illian *et al.* 2008) that are well-suited for the research questions proposed here.

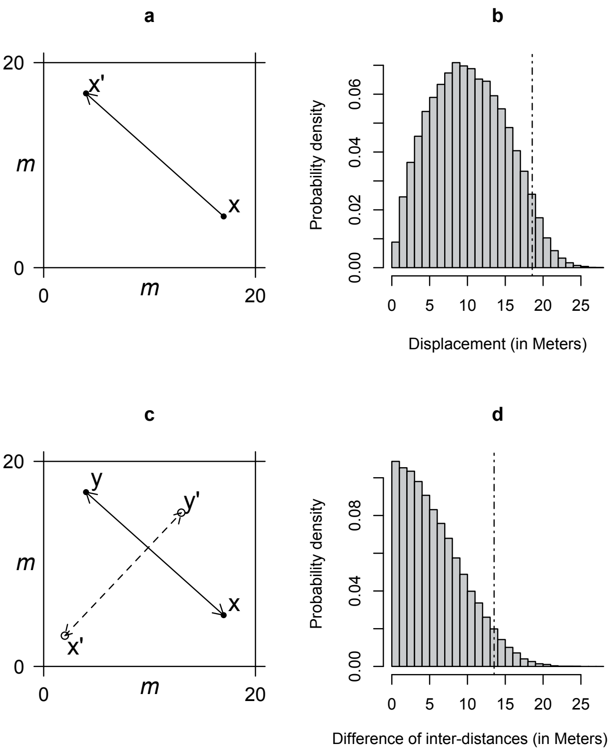

Fig. 31.3. Displacement error (shown as a solid line) between the original (x) and the simulated location (x') of an artefact in a 20 × 20 meter square (**a**). Histogram of the probability density between 100,000 pairs of random points, statistically equivalent to the probability distribution of the displacement errors (**b**). Inter-distance between observed (x and y, solid line) and their simulated counterparts (x' and y', dashed line) in a 20 × 20 meter square (**c**). Histogram of the probability density of the inter-distance between 100,000 pairs of random points (mimicking the original locations of the artefacts) and their simulated counterparts (**d**).

K function

One of the most robust and widely used point-pattern analyses is Ripley's K function (Ripley 1976). This has been applied in a variety of archaeological contexts, from the assessment of site distributions (Bevan & Conolly 2006), to the analysis of intra-site patterning of features (Crema *et al.* 2010) and artefacts (Orton 2004).

The core concept of the analysis is the computation of *K*, equivalent to the mean observed number of *other* points from each *focal* point at a given distance *d*, divided by the overall density of points[2]. This is then compared to the expected theoretical estimate of *K* for a point pattern generated by a given spatial process, which in most cases is a random pattern known as CSR (Complete Spatial Randomness). This becomes effectively a null hypothesis, with the *K* function offering a statistical test for establishing the spatial pattern of a point distribution. At a given spatial scale *d*, if the observed *K* value is higher than the expected *K* we will reject our null hypothesis and consider our point pattern to be *clustered*. Conversely, if the observed *K* is smaller than the expected one, we will have a *dispersed* pattern. The multiple comparisons of the observed and expected values of *K* at different values of *d* can thus allow us to establish the spatial pattern at different spatial scales.

In reality, differences between the observed and the expected *K* will be always present. Thus, the problem will be establishing how much the observed *K* has to deviate from the expected value for correctly rejecting our null hypothesis. The problem can be easily solved through Monte-Carlo simulations, which consists of generating *n* sets of artificial points with the same density of the observed data, but with different and random spatial locations. The *K* value of each set of random points will be then computed, allowing the generation of an envelope of expected values for our null hypothesis. If the observed *K* is outside such a range, the rejection of the null hypothesis (and hence the acceptance of the alternative hypothesis of clustering or dispersion) can be confirmed with a certain level of statistical significance, known also as *p*-value. This will measure the probability of having the observed pattern *if* the null hypothesis was true.

Bivariate K function

A particular instance of *K* function seeks to evaluate, at each distance *d*, the relation between two subsets of a point data in order to determine whether they are *aggregated* or *segregated* to each other (Lotwick & Silverman 1982; Smith 2004). From a methodological standpoint, the bivariate version of *K* is based on the counts of points of type *i* within a given distance *d* from points of type *j*.

The definition of the null hypothesis is slightly more complex in this case and can be broadly distinguished in the following two: *population independence* hypothesis (also known as *random shift* hypothesis) and *random labelling* hypothesis (Goreaud & Pélissier 2003).

The former type aims to evaluate the spatial relation between the outcomes of two independent underlying processes. A typical example is the settlement of a region by two groups of people at two distinct moments in time. The actual envelope of expected *K* values is computed on *n* sets of points derived by randomly "shifting" the

2 The computation of the observed K function will also involve the computation of edge correction weights, which calibrate the effects derived by the reduced number of points at distance *d* when the focal point is located near the edge of the study area. For the present study, we have used Ripley's Isotropic correction (Ripley 1988) for all analysis, except for the bivariate K function with the *population independence hypothesis* where we used Goreaud and Pélissier's formula (Goreaud & Pélissier 1999).

location of one of the two types of the observed data (*Fig. 31.4-b*). This allows the creation of a random set of points with an intrinsic spatial structure identical to the observed one (i.e. the inter-distances between points of the same type will remain unchanged). Such a randomisation technique will allow us to distinguish patterns generated by processes internal to each type from processes derived by the influence of the other type.

The *random labelling* hypothesis is focused instead on the realization of the "mark" (*i.e.* the "type") of each point. In this case, the key assumption is that the process determining the general location of the point data is the same for different types, but the process determining their marks is unknown and needs to be examined. The creation of the envelope of expected *K* values is provided in this case by randomly shuffling the labels of each point, *maintaining* their original spatial location (*Fig. 31.4-c*).

The choice of the null hypothesis is a crucial aspect, since the interpretation of the empirical *K* values are based on their comparison with the theoretical values, which will vary between the two hypotheses. For this study, both two types of null hypotheses have been used. When the distinction between the types was based on chronological marker, we used the *population-independence* hypothesis to establish whether the two discarding process where spatially related. When the distinction was related to the different use of the objects we chose a slightly modified version of the *random-labelling* hypothesis. Our assumption in this case is based on the likelihood that the absolute location of the artefacts (hence the broad variation in the artefact density) was determined primarily by the location of the active agents (humans), whose different *local* behaviour generated difference in the relational structure between different types of objects. To provide a simple example, if we wish to establish the spatial relation between the location of cores and the debris derived by their processing, we cannot consider the two behaviours to be spatially independent. Their location will be determined by *where* the action was performed, and thus an intrinsic spatial dependence should be present in our null hypothesis point pattern. However, further anthropic or non-anthropic activities might generate different spatial structures, leading to higher levels of aggregation or segregation than we would expect from the intrinsic spatial dependency. To formalise this assumption, the random-labelling of the artefact types has been extended to the spatial location of *all* the stone tools recovered in the survey, rather than limiting this to the spatial location of the two types of artefacts assessed each time (*Fig. 31.4-d*). This will remove (and isolate) the "aggregation" derived by the intrinsic spatial dependence linked with the location of the active agents.

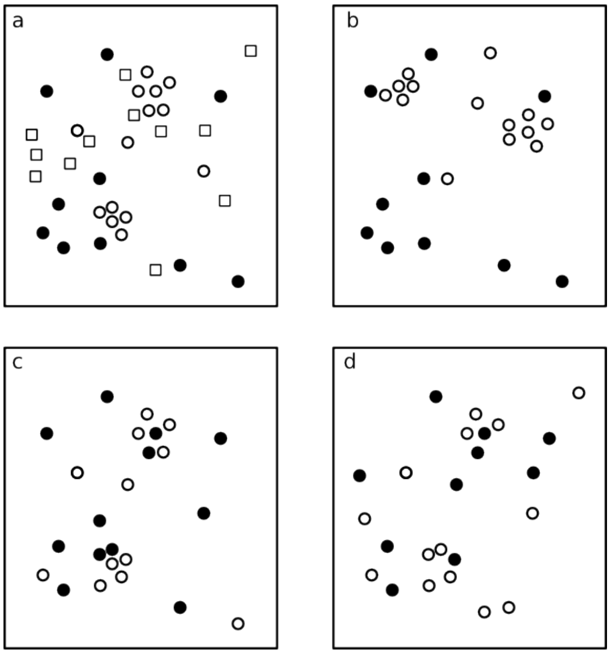

Fig. 31.4. The three types of randomization discussed in the paper. Figure *a* shows the observed locations, with point type A depicted as hollow circles, type B as filled circles and other materials as squares. Figure *b* shows an instance of a random-shift simulation, where the location of points A are shifted, but their internal spatial structure (the inter-distance between each point A to all the other point A) are maintained. Figure *c* shows an instance of random labelling simulation, where the location of points A and B are fixed but their labels are changes. Notice how in both figure *b* and *c* the presence of other materials are ignored. Figure *d* shows our extended version of the random-labelling simulation where *any* location (including those depicted in squares) can be of type A or type B, with the total number of points for each types still maintained.

Local K function

Both univariate and bivariate K functions are regarded as *global* statistics, and as such they describe the average pattern of *all* observed points. This means that a significant clustering (or aggregation) at a specific distance *d* indicates that the *majority* of points have higher than expected values of *K*. Global statistics can however be misleading, especially when we have strong local diversity in the nature of spatial relationships. Consider for example a hypothetic pattern where dispersion and clustering are observed at different locations of the study area. The univariate K function will fail to reject the null hypothesis and we will assume that the pattern is random. From a mathematical standpoint this is correct, as random patterns are by definition characterised by a mixture of both dispersion and aggregation. However global statistics are unable to determine how these two patterns are mixed and *where* they can be observed. A specific combination of patterns could fail to reject a null hypothesis of random

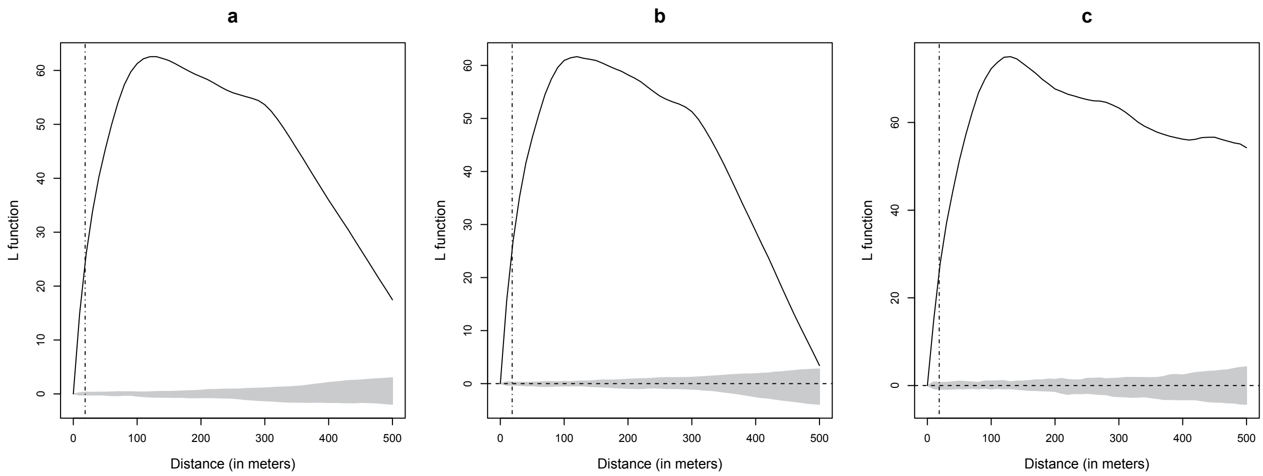

Fig. 31.5. Univariate K functions for the total set of stone tools (a), and subsets corresponding to LSA traditions (b) and MSA traditions. The x-axis represents increasing values of *d* from 0 to 500 meters. The solid line represents the observed L function (a transformed version of K function useful for plotting purposes), while the shaded grey area is the envelope of the null hypothesis of a random pattern generated from the Monte-Carlo simulation with *n*=99. When the solid line is above or below the shaded area the pattern is significantly (with p-value < 0.05) clustered or dispersed. The dotted horizontal line represents the theoretical expected K values, and the dashed vertical lines marks the threshold distance above which the effects of the simulation of the observed data can be ignored.

pattern, but could be still meaningful and significant from an archaeological point of view once we establish *where* the clustering and the dispersion are observed.

A possible solution to this problem is to compute the K function for each observed point, and then plot its own level of significance for the rejection of the null-hypothesis at a given distance *d* (Getis & Franklin 1987; Orton 2004). This will allow us to visualise *where* patterns of clustering and dispersion can be observed, at what level of significance, at what scale, and whether such locations are located at meaningful portions of the study area. The method can also be applied for bivariate data, and will allow us to detect how spatial relationships changes across space, distinguishing, for example, areas where two types of points are highly aggregated from areas where they are segregated.

Results[3]

In order to tackle the three research questions stated in the first section, we analysed the spatial distribution of lithic tools in the case study area. We first assessed the basic univariate pattern of the entire set of stone tools, and then established whether there are any differences between those attributed to Middle Palaeolithic, MSA (Mousterian-Aterian) tradition and those attributed to the Epipalaeolithic/Neolithic, LSA tradition. This first set of analysis allowed us to determine whether the background noise is just a homogenous random scatters of artefacts or not.

The second set of analysis aimed to establish the nature of the spatial relationships between different "types" of artefacts through global bivariate K functions. We reckon that an extremely large number of possible analyses on "types" can be sought. In the present paper, we selected three different aspects of LSA lithic technologies: the choice of the raw material; footprints related to the production stage; and tool functions. Additionally we have also investigated the spatial relation between MSA and LSA tools, testing whether they are spatially independent or not.

The last set of analysis sought to determine whether the patterns detected through the global bivariate K function are homogenous in space or whether different types of relation ("aggregation" and "segregation") co-occur at different locations.

What is the spatial structure of the "background noise"?

Figure 31.5 illustrates the outcome of the univariate K function with the entire data set (5-a), tools attributed to LSA (5-b), and those attributed to MSA (5-c). In all instances the empirical K function indicates a highly

3 All analyses have been computed using R statistical computing language (R Development Core Team 2011). Univariate and bivariate (*random labelling hypothesis*) K functions have been based on the *spatsat* package (Baddeley & Turner 2005), while the bivariate K function with the *population independence hypothesis* has been conducted using the *ads* package (Pélissier & Goreaud 2010). Scripts for the local bivariate K functions have been created using some functionalities of the *spatsat* package, and are available under request.

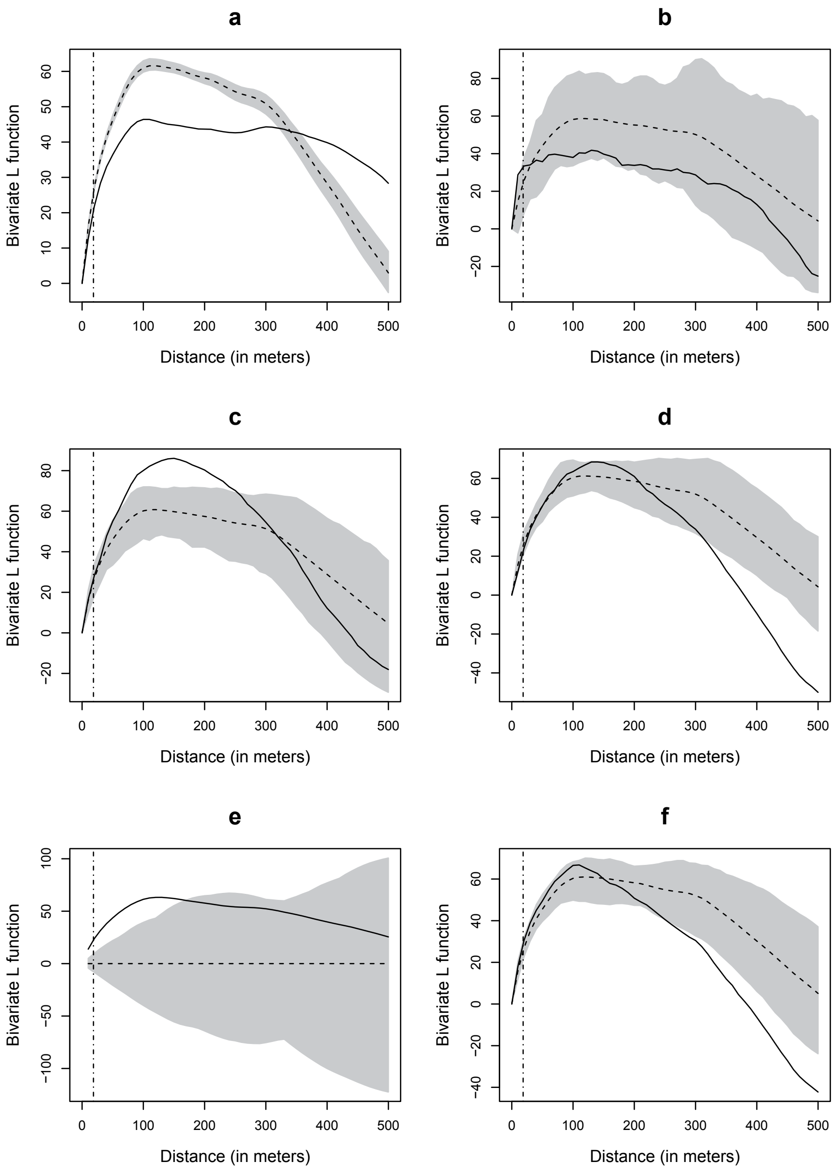

Fig. 31.6. Output of the bivariate L (K) Functions for: (a) Senonian (Gafsa) vs. flints sourced elsewhere; (b) cores and tested raw materials; (c) procurement vs. processing tools; (d) cores and cortices; (e) MSA vs. LSA; and (f) cores vs. debris. As for the univariate function, the solid lines represent the observed L (K) function, the grey shaded area represents the range of expected K values derived from Monte Carlo simulations, and the dashed vertical lines mark the threshold distance above which the effects of the simulation of the observed data can be ignored.

significant clustering at all scales (the solid line is above the grey envelop of the null hypothesis), with marginal differences observed above 300 meters, where different rates of decline in *K* can be observed. This trend reflects the average spatial extent of artefact clusters (compare with *Fig. 31.2*).

Are there any spatial relationships between different types of artefacts?

As mentioned in the 'theory and method' paragraph, two major types of null hypotheses can be tested with the bivariate point pattern analysis. Here, we have adopted the extended version of *random labelling hypothesis* except for the assessment of the relationship between MSA and LSA tools, where we considered the *population independent hypothesis* to be more appropriate.

Choice of raw material

Figure 31.6-a shows the results of the bivariate K function between Senonian flint sourced from Gafsa region (at approximately 200 km) and flints sourced from closer regions (*Oued Marguellil* and *Zeroud*; at *ca* 50 km). The output shows a significant segregation up to 350 meters, followed by a strong aggregation over 400 meters, with a short spatial interval where the relation between the two types can be regarded as random.

Tool production

Figures 31.6-b, *31.6-d*, and *31.6-f* depicts the bivariate K function between cores and tested raw materials (b), cortices (d) and debris (f). In the first case, cores seem to be slightly segregated from the location of the raw materials, although this is never statistically significant. The spatial relation with cortices and debris seems to be similar. In both cases, there is a slight aggregation around

100 meters (although this is not statistically significant) followed by a significant segregation at larger scales, from *ca* 250-300 meters.

Tool usage

Figure 31.6c shows the bivariate K function between tools related to the food procurement (*e.g.* arrowheads, microliths, backed bladelets, etc…) and processing (*e.g.* burins, end-scrapers, side-scarpers, notches, denticulates, etc …). The outcome shows a significant aggregation between the two types of tools at smaller scales (100-200 meters), followed by a random pattern at higher ones.

MSA vs. LSA

Figure 6e shows the outcome of the bivariate analysis between tools of the two periods. The empirical value of *K* exceeds the envelope generated from the *K* values of the randomly shifted points between 100 and 150 meters, indicating a strong aggregation between MSA and LSA lithics at such scales. This relationship is maintained at higher scales but without high levels of statistical significance.

Are there spatial variations in the spatial relationships?

Local bivariate K functions have been conducted to examine the relationship between: 1) Senonian (Gafsa) flints and other flints; 2) cores and tested raw materials/cortices/debris; and 3) procurement tools and production tools. The analyses have been carried out for five intervals of 100 meters, up to 500 meters. For a matter of space, we will discuss and illustrate the outcome of the analysis at the smallest scale of 100 meters, as larger values did not exhibit any meaningful differences. Each map on *Figure 31.7* shows the location of the assessed points (the first set of each pair, thus Gafsa flints, Cores, and procurement tools) with the significance of clustering (upper row) and dispersion (lower row) at 100 meters, depicted with different tones of grey, with darker points representing small values of *p* (more significant patterning).

Choice of raw material

The segregation between Senonian (Gafsa) flints and flints sourced elsewhere suggested by the global bivariate K function (*Fig. 31.6-a*) can be visually assessed in *Figures 31.*7-a and *31.7-b*. The distribution maps show clearly how aggregation is also significant in certain locations. These can be identified in 3-4 clusters roughly corresponding to what has been elsewhere identified as SEK-04, SEK-06, SEK-07, SEK-09, and SEK-10 (see chapter 32 on this volume). Segregation can be instead identified in locations surrounding these clusters (*Fig. 31.7-b*) where Gafsa flints are strongly predominant compared to flints sourced elsewhere.

Footprints of tool production

The local bivariate K functions of cores against tested raw materials (*Figs.* 7-c and 7-d), cortices (*Figs. 31.*7-e and *31.7-f*), and debris (*Figs. 31.*7-g and *31.7-h*) show a complex picture of different relationships between artefact types. As for the global version of the analysis, the locations of cores and tested raw materials appear to show some degree of segregation in three small clusters (*Fig. 31.*7-*d*), while instances of aggregation (*Fig. 31.7-c*) are sporadic and do not appear to be related to specific locations. Interestingly, portions of the study area where cores are significantly aggregated to cortices (*Fig. 31.*7-*e*) correspond to the same places where segregation with raw materials are also evident (*Fig. 31.*7-*d*), while segregation between cores and cortices appears to be mainly confined to the northern part of the study area, with smaller clusters at southern and north-western areas. The relationship between cores and debris follows a similar pattern, although some levels of local diversity are also evident. For example, segregation within the southern cluster appears to match the locations where cores and cortices exhibit significant aggregation, rather than segregation.

Tool usage

The local bivariate K function of the tool usage does not seem to show strong diversification in the spatial relation between procurement and processing tools. Aggregation is predominant in three clusters (*Fig. 31.7-i*) while episodes of segregation (*Fig. 31.7-j*) are sporadic and does not seem to exhibit a spatial structure.

Discussion

The results of the spatial analysis described in the previous section provide grounds to tackle the three research questions posed at the beginning of this paper.

A visual inspection of *Figure 31.2* and the univariate K function strongly supports the impression of clustering in the distribution of lithics, providing both the quantitative measure of the scale where such clustering is peaking and the statistical support for defining the level of significance. While the role of spatial analysis was a merely confirmatory tool for such a research question, both global and local bivariate K functions allowed us to explore intertype spatial relationships that are hardly observable by eyeballing distribution maps.

The most interesting outcome from the global statistics is the significant aggregation between MSA and LSA artefacts. The spatial association could be explained by a number of hypotheses, ranging from convergent effects in the post-depositional processes to shared preference for specific, absolute locations. One possible hypothesis might be related to the re-use of

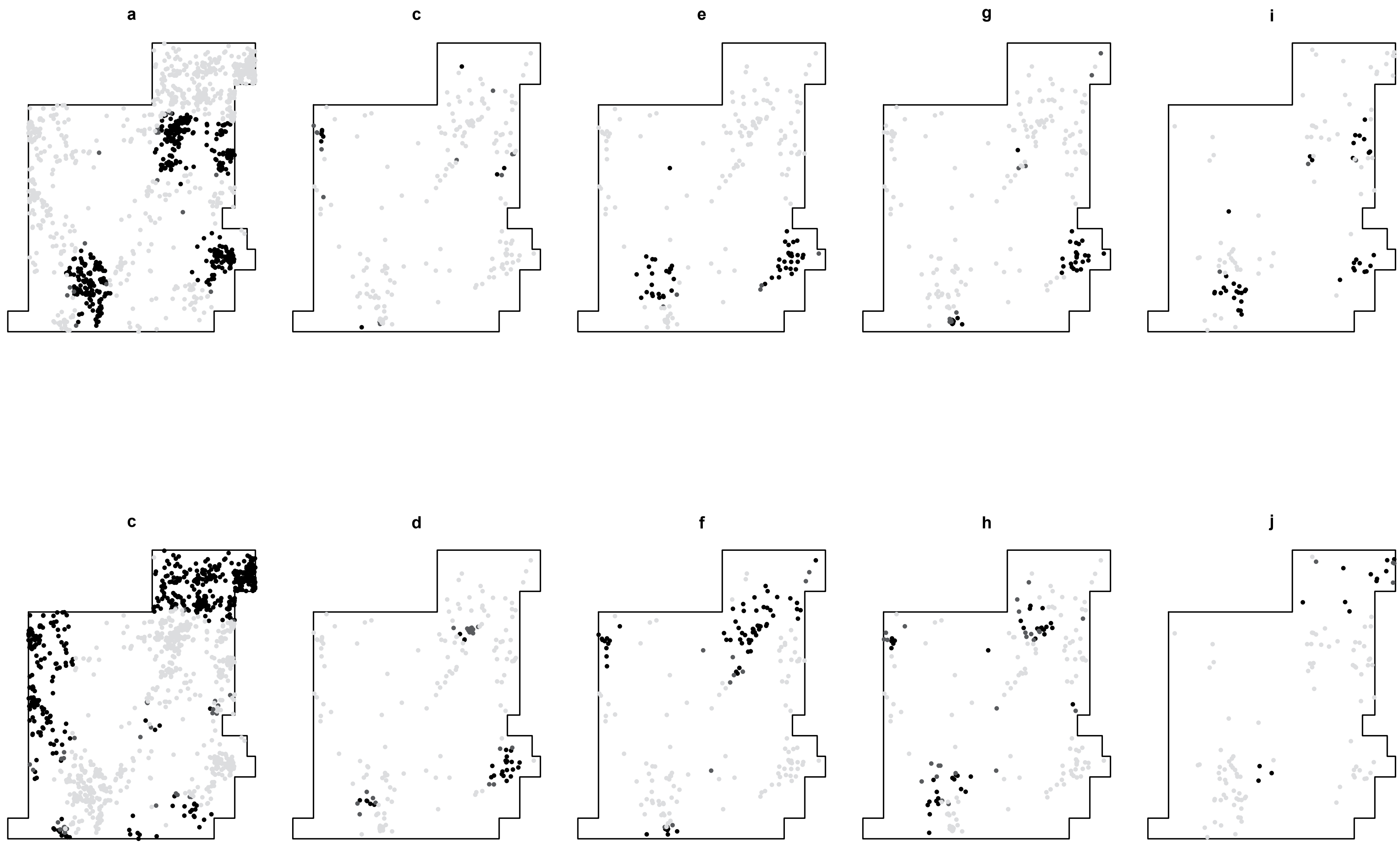

Fig. 31.7. Local bivariate K functions the upper row depicts significance for aggregation while the lower row the significance for segregation for: (a-b) Senonian (Gafsa) vs. flints sourced elsewhere; (c-d) cores and tested raw materials; (e-f) cores and cortices; (g-h) cores vs. debris; and (i-j) procurement vs. processing tools. Black dots are highly significance of (p-value ≤ 0.05), dark-grey dots are mildly significant ($0.05 > p$-value ≤ 0.1) and light-grey points are not significant insignificant (p-value > 0.1).

space by later Epipalaeolithic/Neolithic communities, who might have chosen to settle to locations previously occupied by Middle Palaeolithic communities, where potential tools where "ready to use" (see also Camilli & Ebert 1992). This claim can be supported by the presence of several Middle Palaeolithic artefacts which were re-knapped and re-used (see chapter 32 on this volume), suggesting the possibility that, at some degree, Middle Palaeolithic clusters might have attracted later communities, or alternatively that a large portion of these tools were collected and re-deposited in new locations.

The spatial relation between different artefacts types, and the variation of such a relationship over space sets the basis for evaluating possible diversities between clusters. If we exclude the tools usage, all other inter-type spatial relationships exhibit some form of spatial segregation, indicating how, at least for some locations, one type of artefact was locally dominant compared to the other. Some taphonomic processes (*e.g.* slope erosion, sebkha expansion/contraction) could potentially have different effects on different artefact types (see Allen 1991), as a function of their size and shape. This might have generated apparent clustering of similar artefact types (subject to similar post-depositional forces), and local variation of the post-depositional forces might have generated the observed spatial diversity of the spatial relationships. Although we cannot dismiss this hypothesis, some of the observed pattern appears to have been genuinely determined by episodes of primary or secondary (reuse of artefacts, see above) anthropic depositions. The spatial structure exhibited by different types of flint materials (*Figures 31.6-a*, *31.7-a*, and *31.7-b*), which are likely to be subject to similar post-depositional forces, is perhaps the most remarkable evidence supporting this claim.

The bivariate K function on cores and tested raw materials/cortices/debris illustrates a quite complex picture of spatial interrelationships. Broadly speaking, locations where significant segregation between cores and tested raw materials have been noticed are matching with those where cores-debris and cores-cortices aggregations are evident. This suggests a different use of space in the production stage, with tested raw materials mainly isolated from key clusters of cores, which in turn are closely associated to cortices and debris. A more detailed account of each of these clusters illustrates how different degree of segregation and aggregation can occur at smaller scales. For example, the south-western cluster depicted in *Figures 31.7-e* and *31.7-g* shows how the aggregation between cores and cortices are occurring in the northern part of the cluster, while the aggregation between cores and debris is complementary to this and centred on the southern part.

Conclusion

The adoption of a non-site approach has allowed the exploration of portions of landscapes traditionally neglected in the Tunisian archaeology. The global and local spatial analysis strongly suggests that the background scatters of artefacts surrounding *rammadiyat* are characterised by a complex series of clusters characterised by different composition and proportions of lithic types. Such a structuring will reflect different use of space or different episodes of occupation and could provide important clues on prehistoric communities land-use.

The shift of the unit of analysis marks a critical and flexible point of departure in this regard. While a site-based approach will ultimately lead to a loss of information generated by an imposed aggregation of information, artefact-based approaches maximise the available information so that multiple and contrasting aggregation criteria can be adopted. Bivariate local K function has shown that a single cluster of artefacts can be characterised by internal subdivisions where the spatial relationship between artefacts types differ. Crucially this will be a function of the chosen pair of types. One might exhibit a homogenous relationship within the cluster, while another pair might show diversity.

More in general, our work suggests that we should not ignore the presence of consistent human activities outside the *rammadiyat*. The superficial nature of these off-site locations does not allow the creation of precise chronological frameworks derivable from the stratigraphic relationships defined in excavation contexts. Hence a different set of research directions suited for approaching such datasets is required. The spatial dependence of Epipalaeolithic/Neolithic communities to previous Middle Palaeolithic locations is perhaps the best example we can provide on this regard. A site-based survey would be insufficient for claiming such a hypothesis, and a simple excavation would only allow a marginal window of observation for suggesting the existence of such behaviour. Only an extensive, artefact-based survey allows us to detect such patterns.

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